

EXHIBIT 1

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**UNITED STATES DISTRICT COURT
NORTHERN DISTRICT OF CALIFORNIA
SAN FRANCISCO DIVISION**

IN RE UBER TECHNOLOGIES, INC., PASSENGER SEXUAL ASSAULT LITIGATION

Case No. 3:23-md-03084-CRB

CORRECTED SUPPLEMENTAL REPORT OF JOHN CHANDLER, Ph.D.

This Report relates to the following Wave 1 Cases:

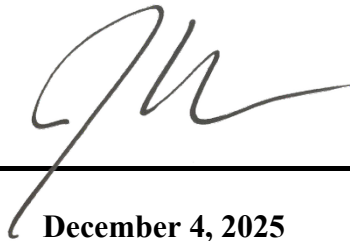
Case No. 24-cv-7940 (B.L.)

Case No. 24-cv-7821 (A.R.2)

Case No. 24-cv-7019 (LCHB128)

Case No. 23-cv-6708 (Dean)

Case No. 24-cv-4900 (WHB 832)



December 4, 2025

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I. Background, Qualifications, and Experience

1. I am an Assistant Professor of Data Science at the University of St. Thomas and received a Ph.D. in Statistics from the University of Montana in 2010. I have worked professionally in data science since 1999, before the term was coined. I was a Clinical Professor of Marketing at the University of Montana for 10 years, teaching marketing classes, and have been a practitioner of marketing for twenty-five years.

2. I submitted an opening report (“Opening Report”) in this matter on September 26, 2025, and a rebuttal report (“Rebuttal Report”) on October 24, 2025. My background, qualifications, and experience are described in paragraphs 1 through 16 of my Opening Report. I hereby incorporate and adopt by reference my Opening Report and my Rebuttal Report.

II. Assignment

3. I have been asked to draw on my industry background and academic expertise to supplement my Opening Report with analysis based on the recently provided Flack data and Flack deposition. I have been asked to perform the following analyses:

- Review the recently produced Flack data to determine whether it changes any of the analysis of my Opening Report.
- Utilize the recently produced Flack data to calculate the relative risk of sexual assault or sexual misconduct for Uber riders when taking into account documented risk factors such as the hours of rides (day or night) and day of week (weekdays or weekends).
- Utilize the recently produced Flack data to calculate the relative risk of sexual assault or sexual misconduct for each of the five bellwether scenarios at the time of the incident.
- Utilize the recently produced Flack data to estimate the rate of underreporting to Uber and estimate the true number of sexual assault and sexual misconduct on the Uber platform.
- Utilize the recently produced Flack data to evaluate whether the incident rates across 2023-2024 are increasing or decreasing relative to prior safety reports.¹
- Utilize the recently produced Flack data to evaluate reports of sexual assault and sexual misconduct prior to January 1, 2017.
- Utilize the recently produced Flack data to estimate the total number of incidents.
- Utilize the recently produced Flack data to conduct repeated exposure analysis for the demographic of young women on a nighttime ride.

¹ I was not provided with data for 2025.

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4. A list containing additional materials relied upon is included in Appendix A. Any code I used to analyze the newly produced Flack data is provided in bucket1m in Uber's AWS system.

III. Summary of Opinions

- 1) None of the analytical opinions from my Opening Report change when I recreate them using the Flack data.
- 2) Flack data contain incident-level data whereas my Opening Report Incident Data contained only counts of incidents by month.
- 3) The additional fields available in the Flack data make it possible to estimate certain aspects of relative risk, particularly in where Uber has provided ride-level information.
- 4) While the Flack data allows estimation of many types of relative risk, Uber has not disclosed ride-level information that would be needed to support that analysis. In those situations, I can use the Flack data to illustrate relative risk concepts by looking at, for instance, the relative risk of an incident escalating from sexual misconduct to sexual assault.
- 5) Uber had access to information about and analyzed a wide set of significant variables that would have allowed the company to develop relative risk levels for high-risk circumstances. Generally, Uber has not disclosed that information.
- 6) The Flack data is limited and does not include many facets of rides, riders, and drivers that Uber has documented influence the risk of a sexual assault on a ride.
- 7) Since the publication of Uber's most recent safety report, the rate of sexual assault and sexual misconduct on the platform has risen.
- 8) Based on the Flack data, Uber could have calculated the elevated risk faced by riders under high-risk conditions—late-night trips, weekend trips, female riders paired with male drivers.
- 9) These elevated per-trip risks can be combined with realistic usage patterns to estimate a rider's annual probability of experiencing at least one driver-initiated incident.
- 10) Across realistic late-night usage patterns—20, 50, and 120 trips per year—a female rider with male drivers faces an annual probability of experiencing at least one incident of sexual misconduct ranging from approximately 1 in 40 to 1 in 7.
- 11) For sexual assault specifically, the corresponding annual probability ranges from approximately 1 in 467 to 1 in 78 under the same high-risk conditions.
- 12) These cumulative-risk estimates demonstrate that even small per-trip probabilities translate into meaningful annual risks when riders rely on Uber for nighttime

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transportation—risks Uber could have quantified and disclosed using the data in its possession.

- 13) The repeated-exposure analysis in the Flack data confirms my prior conclusion that Uber did not incorporate its own knowledge of relative risk into meaningful rider-facing warnings or protective practices.
- 14) Taken together, the Flack data confirm that Uber possessed the information necessary to understand the elevated dangers facing riders, especially young women on late-night rides, and did not use this information to reduce or disclose those risks.

IV. Flack Data Comparison to Numbers in Opening Report

5. To evaluate whether the newly produced Flack incident data materially changes the analyses presented in my Opening Report, I first compared the monthly number of sexual assault and sexual misconduct incidents in the Flack data to the corresponding counts in the previously produced incident report data 2017–2024 (“Opening Report Incident Data”), the data available at the time of my Opening Report.

6. This comparison yields the following conclusions:

- 1) Perfect agreement in 83 of 84 month-level counts (Jan 2017–Dec 2023). For every month from January 2017 through November 2024, the number of incidents in the Flack data matches exactly the number of incidents in the Opening Report Incident Data.
- 2) A single discrepancy occurs in December 2024. The Opening Report Incident Data included incident counts only through December 30, 2024, whereas the Flack data includes December 31, 2024. The missing final day, [REDACTED], explains the entirety of the discrepancy. I observed no other differences from 2017 through 2024.
- 3) The Flack data include more incident records than the earlier production because the Flack data include a longer time range. The Flack records begin on October 6, 2013.² In total, there are [REDACTED] in the Flack data, [REDACTED] more than in the Opening Report Incident Data.
- 4) The Flack data contain substantially more information per incident. The Opening Report Incident Data consisted solely of counts by incident type and month, without trip-level detail. In contrast, the Flack data include the following:
[REDACTED]

² Throughout this report, I will use the field “trip_request_time_local” to estimate times. This field includes both dates and times of the trips with incidents.

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- [REDACTED]
 - Alleged assailant classification fields.³
- 5) These additional fields are necessary to compute relative risks, evaluate time-of-day and assailant patterns, and reproduce Uber's internal assailant classification logic
 - 6) No analytical conclusions in my Opening Report change because of the newly produced Flack data.
 - 7) After excluding the single additional day (Dec 31, 2024), the Flack data reproduce the counts from the incident report data 2017–2024 exactly. The expanded fields in the Flack data allow for more detailed analyses (e.g., assailant, night/weekend, city-level patterns), but they do not alter any conclusions regarding the number or distribution of incidents over time.

V. Relative Risk Analysis of Incidents for Uber Riders under Specific Conditions

7. As I discuss in my Opening Report, Uber created an internal tool, the Safety Risk Assessed Dispatch (“S-RAD”) tool, to improve safety related to sexual assault or misconduct. Uber's internal S-RAD tool purports to estimate the riskiness of specific trips based on factors such as time of day, day of week, pickup location, driver history, and passenger behavior.⁴ This tool was considered confidential,⁵ and Uber stated in the project brief that “unplanned disclosure of the tool could have significant reputational ... implications.”⁶ Throughout the history of S-RAD, Uber expresses concern for the potential brand damage caused by public acknowledgement of the tool. Ultimately, this brand concern caused Uber to keep the information secret, preventing potential benefits to Uber's riders, including Jaylynn Dean, [REDACTED] (“Plaintiffs”).

8. At the time that I submitted my Opening Report, Uber had not provided data necessary to recreate, even partially, the insights from the S-RAD model, which would allow me to illustrate what Uber could have disclosed.⁷ Since then, Uber has provided information through

³ Uber did not produce a single “alleged assailant” field. The Flack data include four fields—[REDACTED]—from which an assailant classification can be derived. The details of my alleged assailant variable creation appear in Appendix B.

⁴ UBER_JCCP_MDL_002658347 at 8349. [PRD] SRAD nudges to trigger safety preferences configuration (May 22, 2024).

⁵ UBER_JCCP_MDL_003398058. Email from Danielle Sheriden [dportugal@uber.com] to William-all-directs [William-all-directs@uber.com] re “Follow Up: Personal Safety Roadmap (H2 2018).” July 10, 2018 at 11:37 PM.

⁶ UBER_JCCP_MDL_001738115. What is S-RAD? (May 21, 2019).

⁷ Sonny Wong Dec. Sept. 4, 2025. This document states that Uber has not produced S-RAD scores for 300,000 of the 400,000+ incidences in the Safety Data.

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newly accessible Flack data, and the Flack deposition and exhibits of Todd Gaddis taken on November 7, 2025, which allowed me to do a more comprehensive risk assessment for the relative risk levels for Uber customers in specific conditions.

9. With the data that Uber has subsequently provided, I offer a risk assessment that illustrates the level of relative risk for Uber customers under specified conditions.

10. Before describing my analysis, I briefly explain the concept of relative risk. Disclosing relative risk is a common tactic in public health, letting consumers know the implications of activities like smoking,⁸ driving without a seatbelt,⁹ or being struck by lightning.^{10,11} Relative risk is a critical measure in decision-making, telling an audience how much risk can be mitigated by changing behavior or making different choices.

11. Uber's internal documents recognize that the risk of sexual assault and sexual misconduct varies systematically with factors such as time of day and day of week. In an April 2019 slide presentation discussing disclosures around safety, Uber employees discussed sharing date and time information.¹² Uber acknowledged that this information "[w]ould serve as a 'compromise' for consumers looking to learn more on how to manage their safety." This knowledge, however, involved trade-offs for Uber. The slide goes on to state that this disclosure would have had "[s]erious business implications" and disclosure "prompts users to ask what Uber is doing to mitigate safety concerns during peak hours." Ultimately, the slide concludes succinctly: "Recommendation: No."

12. Despite its stated unwillingness to share this data with consumers, Uber had access to information that demonstrated the utility of examining risk factors associated with sexual assault. Uber developed a machine learning product, S-RAD, to estimate the probability of a sexual

⁸ Pesch, B., Kendzia, et al. (2012). "Cigarette Smoking and Lung Cancer—Relative Risk Estimates for the Major Histological Types from a Pooled Analysis of Case-Control Studies." *International Journal of Cancer*, vol. 131 no.5, pgs. 1210-1219. <https://doi.org/10.1002/ijc.27339>.

⁹ National Highway Traffic Safety Administration. "Seat Belts." Accessed on Sept. 10, 2025. <https://www.nhtsa.gov/vehicle-safety/seat-belts> ("If you buckle up in the front seat of a passenger car, you can reduce your risk of: Fatal injury by 45% (citing Kahane, C. J. (2015). "Lives Saved by Vehicle Safety Technologies and Associated Federal Motor Vehicle Safety Standards, 1960 to 2012." Report No. DOT HS, 812, 069).).

¹⁰ Holle, R. L., Brooks, W. A., & Cummins, K. L. (2021). "Lightning Occurrence and Casualties in US National Parks." *Weather, Climate, and Society*, vol. 13 no. 3, 525-40.

¹¹ I do not offer lightning strikes as an appropriate comparator for sexual-misconduct risk on Uber. I reference it here only because Defendants' expert invoked lightning as contextual framing. My point is simply that, even accepting their chosen analogy for the sake of argument, Uber does not provide consumers with risk information at the level that their analogy would imply. Nothing in this report should be read as endorsing lightning strikes as a meaningful basis for assessing platform safety.

¹² UBER_JCCP_MDL_001720345 at 0353. Project - T Business Decisions (Apr. 18, 2019).

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assault or sexual misconduct arising from a pairing of a given driver and rider.¹³ The tool used historical information about the rider and driver and included “trip attributes such as pickup location, time of day, and day of week; and whether the rider and driver genders are the same or different.”

A. Elevated Assault Risk above Misconduct Baseline

13. Because Uber has not provided ride-level counts by hour of day and day of week, I cannot compute an absolute per-ride risk (for example, “1 in 20,000 overall vs. 1 in 4,000 at a specific hour”). However, the Flack incident data do allow me to examine relative risk of escalation—that is, how the balance between sexual misconduct (“SM”) and sexual assault (“SA”) changes under different conditions. This analysis relies upon only Uber’s own Flack raw incident records.¹⁴

14. Using the Flack data, I constructed a weekly grid with 24 hours for each of the 7 days of the week (168 hour-of-week cells). For each incident, I used Uber’s trip timestamp and time-zone information to assign a local day of week and hour of day. I then restricted attention to incidents that Uber classified as sexual misconduct or sexual assault and that were reported against the driver, because those are the incidents most relevant to the Plaintiffs.

15. For each hour-of-week cell, I counted the number of sexual misconduct incidents reported against drivers and the number of sexual assault incidents reported against drivers. Across all hours of the week combined, there are roughly ten sexual misconduct incidents for every sexual assault in the Flack data. I treat this overall ratio as a baseline measure of severity.¹⁵ For each hour and day of the week, I then compute two quantities:

- The SA:SM ratio for that cell (number of sexual assaults divided by number of sexual misconduct incidents in that cell); and

¹³ Sonny Wong Dep. Apr. 16, 2025, Ex. 2829 (UBER_JCCP_MDL_001738115 at 8115. S-RAD Comms Recommendation (May 2019)).

¹⁴ The Flack production includes fields labeled for Zendesk ticket identifiers, but in the records available to me those fields are uniformly empty. In deposition, Mr. Gaddis testified that Flack may at one point have captured a broader set of incident reports, and also that Flack only records incidents for which Uber can “reasonably identify” the underlying trip. As a result, incidents where a reporter conveyed that a rider, family member, or friend was assaulted but did not (or could not) provide enough information to match the report to a specific trip would not appear in the Flack data reviewed for this analysis. In this way, the Flack data represents a lower bound on incidents on the platform and a subset of the information Uber could have tracked related to incidents.

¹⁵ This is not to say that the Sexual Misconduct categories are not serious. Uber’s Sexual Misconduct taxonomy includes a wide range of behaviors, some of which are inherently serious—for example, “Verbal Threat of Sexual Assault,” “Self-Touching/Indecent Exposure,” “Soliciting Sexual Act,” and “Indecent Photography/Videography Without Consent.” My analysis treats each category according to Uber’s own internal definitions, but noting this range of severity does not meaningfully alter any of the quantitative results presented here, including estimates of overall incident rates or relative risks.

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- A relative risk index, defined as the cell-specific SA:SM ratio divided by the overall SA:SM ratio.

16. A relative risk index of 1.0 means that the balance between assaults and misconducts at that hour is the same as the overall balance. A value of 2.0 means that sexual assaults are occurring twice as often relative to misconduct as they do overall; a value of 3.0 means assaults are occurring three times as often relative to misconduct as they do overall.

17. The pattern in Uber’s own data is striking. The relative risk of escalation from sexual misconduct to sexual assault is not uniform across the week:

- Late-night and early-morning hours show the highest escalation risk. In particular, the relative risk index exceeds 2.0 for many hours between approximately 1:00 a.m. and 4:00 a.m., meaning that during those hours, sexual assaults are more than twice as common relative to misconduct as they are overall.
- The elevation is especially pronounced on weekend nights and early weekend mornings. Around the early morning hours of Saturday and Sunday, the relative risk index reaches values greater than 2.5, and in the highest-risk cells approaches roughly 2.7. In practical terms, that means that, in those hours, a rider who experiences a sexual incident with a driver is more than two-and-a-half times as likely for that incident to be classified as a sexual assault rather than sexual misconduct, compared to the average across all times of the week.
- By contrast, daytime hours on weekdays show substantially lower relative risk, with indices at or below 1.0—indicating that incidents during those times are less likely to escalate to sexual assault, relative to the overall baseline.

18. These patterns are consistent with the concerns reflected in Uber’s internal documents about “peak hours.” Uber’s own incident data show that certain late-night trips, especially those during weekend periods are dramatically more dangerous, in terms of the severity of rider-reported sexual incidents, than the overall average Uber trip across all times. Yet Uber did not disclose even this kind of high-level relative-risk information to riders.

19. Had Uber shared these patterns—for example, by warning riders that late-night trips, especially late-night weekend trips carry more than twice the typical risk that a sexual incident will escalate to sexual assault—riders such as the Plaintiffs could have made different safety choices: they might have avoided or limited trips during the high-risk windows, changed how they used Uber in those periods, or made more informed decisions about whether and how to ride at those times. Uber’s decision to withhold this information, despite possession of information that relative risk varies sharply over the week, deprived riders of tools they could have used to manage their safety.¹⁶

¹⁶ Color-coded risk systems are a standard tool used by public agencies and safety regulators to communicate relative danger in a clear, accessible way. For example, the National Weather Service uses green–yellow–orange–red–purple scales to convey the severity of storms and other hazards; the Environmental Protection Agency’s Air Quality Index similarly ranges from green (“Good”) to maroon (“Hazardous”); FEMA employs green–yellow–orange–red tiers for activation levels; hospitals

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20. This analysis also underscores a broader point I made in my Opening Report: Uber’s public Safety Reports present data in a way that minimizes perceived risk rather than equipping riders to understand it. Relative-risk calculations based on Uber’s own incident data would have allowed riders, including the Plaintiffs, to understand when they faced substantially heightened risk and to act accordingly.

21. To visualize the relative risk throughout the week, I have created the following chart. In it, we can clearly see the times of the week when the relative risk of sexual assault, compared to the sexual misconduct baseline, is the highest: late at night, particularly on weekends.

use green–yellow–red–black surge levels to signal resource strain; and widely adopted triage-tag systems classify patient urgency as green (“Minor”), yellow (“Delayed”), red (“Immediate”), and black (“Expectant”). These systems reflect a consistent practice across domains: when relative risk varies meaningfully, institutions provide the public with simple, graded warnings to support informed decision-making. My review of the Flack data has provided me a partial view into how Uber could have built similar systems.

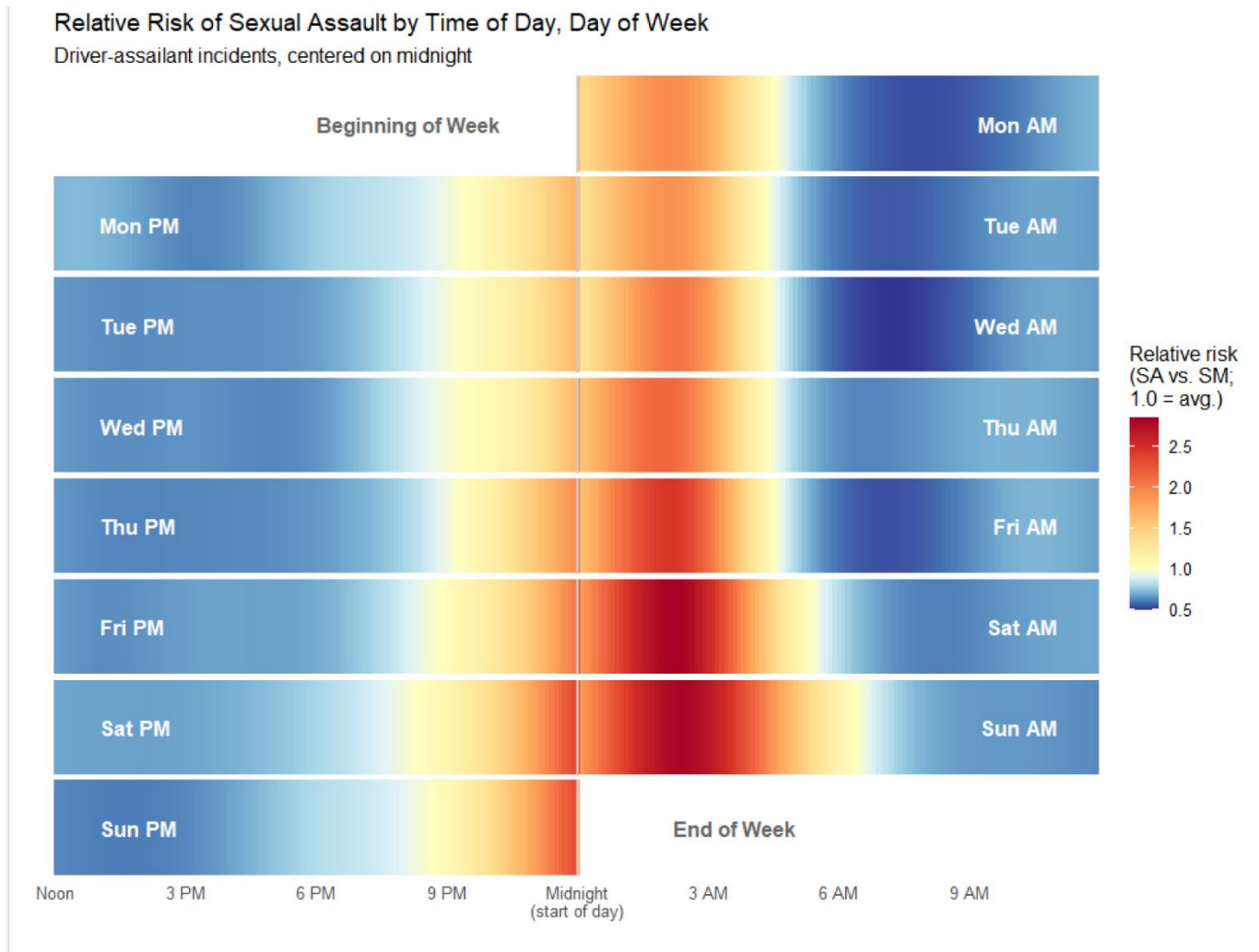
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Figure 1. Heat map of risk by hour of day and day of week. Red areas display a higher risk travel times while blue areas are safer times to travel.

22. To summarize these patterns in a simpler way, but including uncertainty estimation, I grouped trips into three time-of-week categories that correspond to typical usage. I define “weekend nights” as trips occurring on Friday night (from 10 p.m. Friday through 4 a.m. Saturday) or Saturday night (from 10 p.m. Saturday through 4 a.m. Sunday). I define “weeknights” as Sunday through Thursday nights (from 10 p.m. through 4 a.m. the following calendar day). All other hours are grouped as “other times.” This is similar to how Uber has defined nights for internal analysis.¹⁷

¹⁷ UBER_JCCP_MDL_003618304. S-RAD Phase 2: Main Results (Aug. 2019). This analysis done by Uber separates 10pm-4am from the rest of the day; and, UBER_JCCP_MDL_000555196. Night Trip Definition (Feb. 25, 2022) (“I would like to propose the definition of a night trip between the hours of 11pm and 5:59am.”).

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23. Using Uber's incident data, I calculated, for each category, the ratio of sexual assaults to sexual misconduct incidents and compared that ratio to the overall assault-to-misconduct ratio across all times of the week. The resulting relative-risk estimates are shown in the figure below, with 95 percent confidence intervals. In Uber's own data, sexual incidents that occur on weekend nights are approximately 2.03 times as likely to be classified as sexual assaults rather than sexual misconduct, relative to the average across all times of the week (95% confidence interval [1.99, 2.08]). Sexual incidents on weeknights have a relative-risk estimate of 1.52 (95% CI [1.48, 1.55]). By contrast, incidents that occur during other times of the week have a relative-risk estimate of 0.73 (95% CI [0.725, 0.75]), meaning that outside late-night periods incidents are substantially less likely to escalate to sexual assault.

24. This three-group summary shows the same pattern as the hour-by-hour heatmap: in Uber's data, the risk that a sexual incident will escalate to sexual assault is markedly higher during late-night weekend periods, elevated (but lower) on other late-night trips, and lowest during daytime and early-evening hours.¹⁸ These are precisely the kinds of patterns Uber could have disclosed to riders to help them understand when sexual incidents on the platform are most likely to be severe.

25. Although Uber's own data show that the risk of sexual assault rises sharply during late-night weekend hours, Uber did not publicly report safety information at this level of detail. Instead, its public reporting presented a single, aggregated metric that combined the safest and most dangerous periods of the week. This had the practical effect of diluting the high-risk periods with the much larger number of low-risk trips, thereby materially understating the true risk riders faced during the hours when assaults were most likely to occur.

¹⁸ My work here is based on the relative risk of Sexual Assault versus Sexual Misconduct, the underlying Flack data show that all incident types—Sexual Misconduct as well as Sexual Assault—cluster disproportionately in the same late-night and weekend periods. In other words, the elevated risk visible in the charts in this section is not unique to Sexual Assault; overall incident volumes follow a similar temporal pattern. Without the detailed ride information, which Uber has access to but has not produced, it is not possible to illustrate this risk distribution.

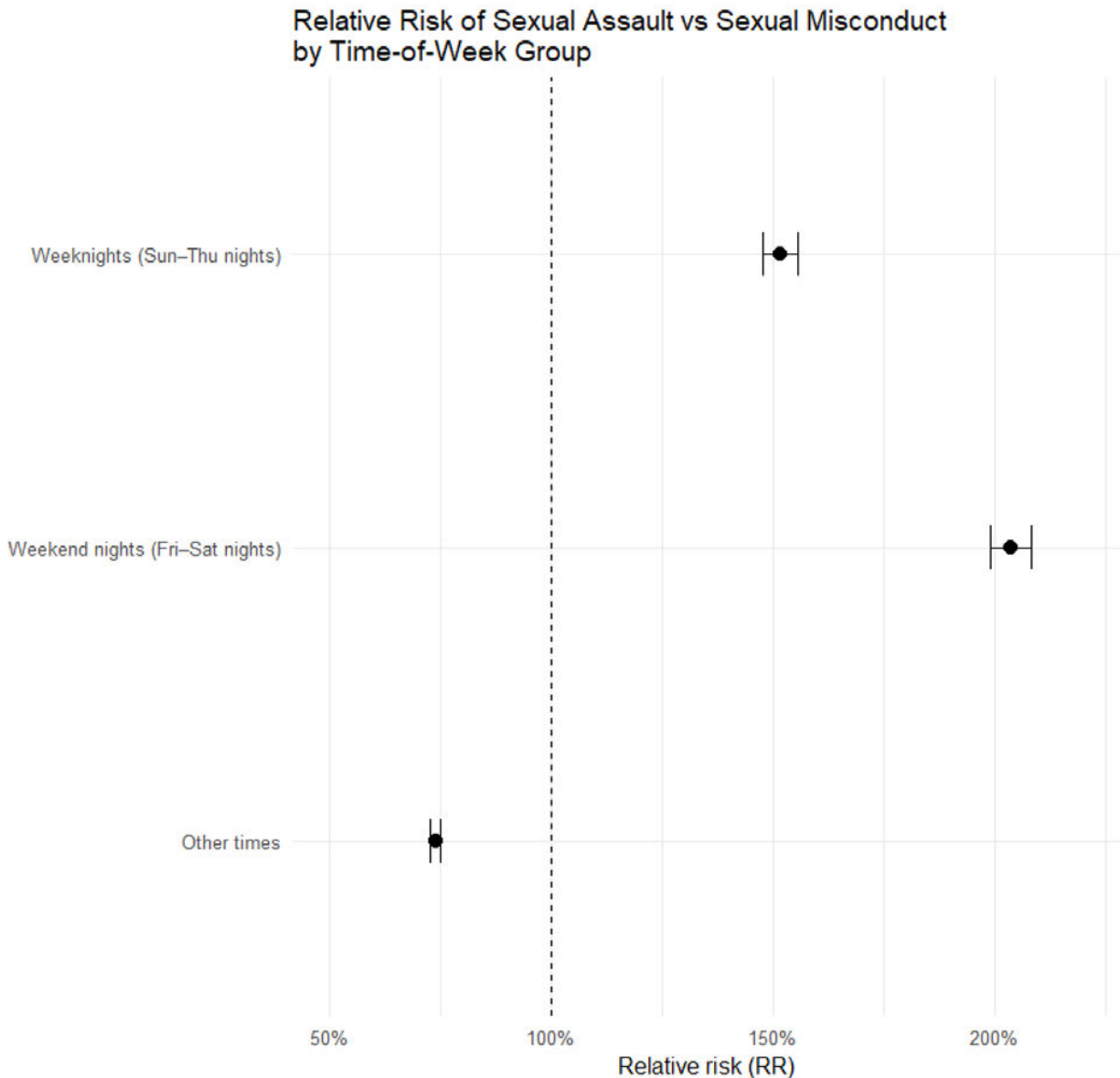
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Figure 2. Relative risk of reported sexual assault compared to sexual misconduct across three time-of-week categories. Points represent estimated relative risks (RR), and horizontal bars show corresponding confidence intervals.

B. Relative Risk Analysis of Sexual Assault for Uber Riders

26. The escalation analysis in the previous subsection shows that when a sexual incident occurs, it is far more likely to be classified as sexual assault rather than sexual misconduct during weekend late-night hours. Because Uber has not shared detailed ridership data by time of day, however, that analysis necessarily used escalation from misconduct to assault as the baseline. In this subsection, I calculate relative risk using a different baseline: the number of Uber rides. Uber has produced limited ride-volume data that break out the number of rides taken during

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weekday and weekend periods for each year and each state.¹⁹ These data—though incomplete—allow for a direct estimate of the probability that a ride taken during a given portion of the week results in sexual assault.

27. This analysis does not depend on the relative proportions of sexual assault and sexual misconduct; instead, it measures the per-ride risk of sexual assault. By comparing the number of sexual assaults in a given state and time-of-week category to the corresponding number of rides, I can estimate the true risk riders faced during weekend periods versus other times of the week. Because Uber did not provide ride information by time of day, it is not possible to separately analyze the especially dangerous late-night period identified in the previous subsection; the estimates here therefore represent a conservative measurement of risk.

28. Even with these limitations, the results show the same pattern identified in Uber's incident-severity data: weekend rides carry substantially higher per-ride sexual assault risk than rides taken during other times of the week. This pattern holds not only nationally but also in the three states relevant to the bellwether plaintiffs—California, Arizona, and North Carolina—demonstrating that the elevated weekend risk was fully present in the jurisdictions where these plaintiffs used Uber.

29. To estimate the per-ride risk of sexual assault during weekends compared to weekdays, I combined several independent sets of data produced by Uber. I used Uber's incident-level Flack data described above to get counts of reported incidents by trip date, time, city, and alleged assailant type. From these records, I identified all driver-assailant sexual assaults and assigned each incident to a weekday or weekend period based on the date of the trip. I also used Uber's statewide ridership volumes, which break out the number of rides taken during weekday and weekend periods by state and by year. Finally, Uber provided mappings between cities and states.²⁰ By integrating incident counts from the Flack data, mapped to states, with ride volumes from the ridership dataset, I calculated the per-ride sexual-assault rate for weekday and weekend trips in every state and year for which Uber provided data. These two components—incident counts and ride denominators—together provide the basis for computing the relative risk of weekend versus weekday rides.

30. Across all years and states for which Uber provided data, weekend rides consistently showed higher per-ride sexual-assault risk than weekday rides. Aggregating nationally, the estimated risk of sexual assault per ride was 38%–74% higher on weekends compared to weekdays, depending on the year. This elevated weekend risk appears in every state, including all three bellwether states. In California, weekend rides were approximately 1.5 to 1.8 times more likely to result in sexual assault than weekday rides; Arizona and North Carolina show similarly elevated weekend risks. Because these estimates average over all hours of the day—and cannot isolate the especially high-risk late-night period identified earlier—they understate the true difference in risk between weekend and weekday rides. Even so, the pattern is unmistakable:

¹⁹ Todd Gaddis Dep. Nov. 7, 2025. Ex. 1574. State & Weekend Data.

²⁰ UBER_JCCP_MDL_005550300.

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weekend rides carry substantially greater sexual-assault risk than rides taken during other portions of the week, both nationally and within the bellwether states.

31. In every year in the Flack data since 2017, the per-ride driver-assailant sexual-assault rate is 38% to 73% higher on weekends than on weekdays (2017: 73%; 2018: 71%; 2019: 62%; 2020: 45%; 2021: 51%; 2022: 38%; 2023: 46%; 2024: 43%).

32. I have access to additional ride information from Uber that I can use to estimate risks of sexual assault. Gender plays an important role in sexual assault, with 90% of sexual assault victims being women, according to Uber's Safety Reports.²¹ Similarly, the vast majority of assailants are men.²² Uber does not generally collect information on the gender of riders, and estimates from surveys range widely. To be conservative, I will assume that half of riders are women, though Uber has produced estimates that the true fraction is closer to one in three.²³ This assumption reduces the estimated per-ride risk for women compared to what it would be if women made up a smaller share of riders, and therefore favors Uber.

33. These data can be layered together to illustrate the risks to women taking rides on Uber's platform on weekends. I begin with the national per-ride weekend sexual-assault rate estimated in the previous analysis and then scale that rate to reflect that nearly all reported victims are women, but women make up a smaller fraction of riders. I then further adjust the rate using Uber's driver-census data, which show that the majority of Uber drivers are men in every year for which data are available. This yields two quantities: the per-ride weekend risk of sexual assault for an average woman rider, and the per-ride weekend risk for a woman who is matched with a male driver.

34. To make these risks concrete, I express them relative to the baseline national per-ride assault risk for all riders. The baseline rate answers the question, "Out of all Uber rides, how often does any rider report sexual assault?" The female-adjusted rate answers, "How often does this happen to women riding on a weekend specifically?" The female-plus-male-driver rate answers, "How often does this happen to women riding on a weekend with male drivers?" As shown in the chart below, the risk to women on weekend rides is several times higher than the baseline rate for all riders, and higher still when focusing on rides with male drivers.

35. Relative to the national per-ride weekend baseline for all riders, women riders faced approximately a 1.8x elevated risk of sexual assault, and women riding with male drivers on weekend trips faced at least a 2.4x elevated risk over the 2013–2024 period.

²¹ UBER_JCCP_MDL_003561529. Uber US Safety Report (2021-2022).

²² UBER_JCCP_MDL_000418750.

²³ Gaddis Dep. Ex. 1576. Rider Sex Data.

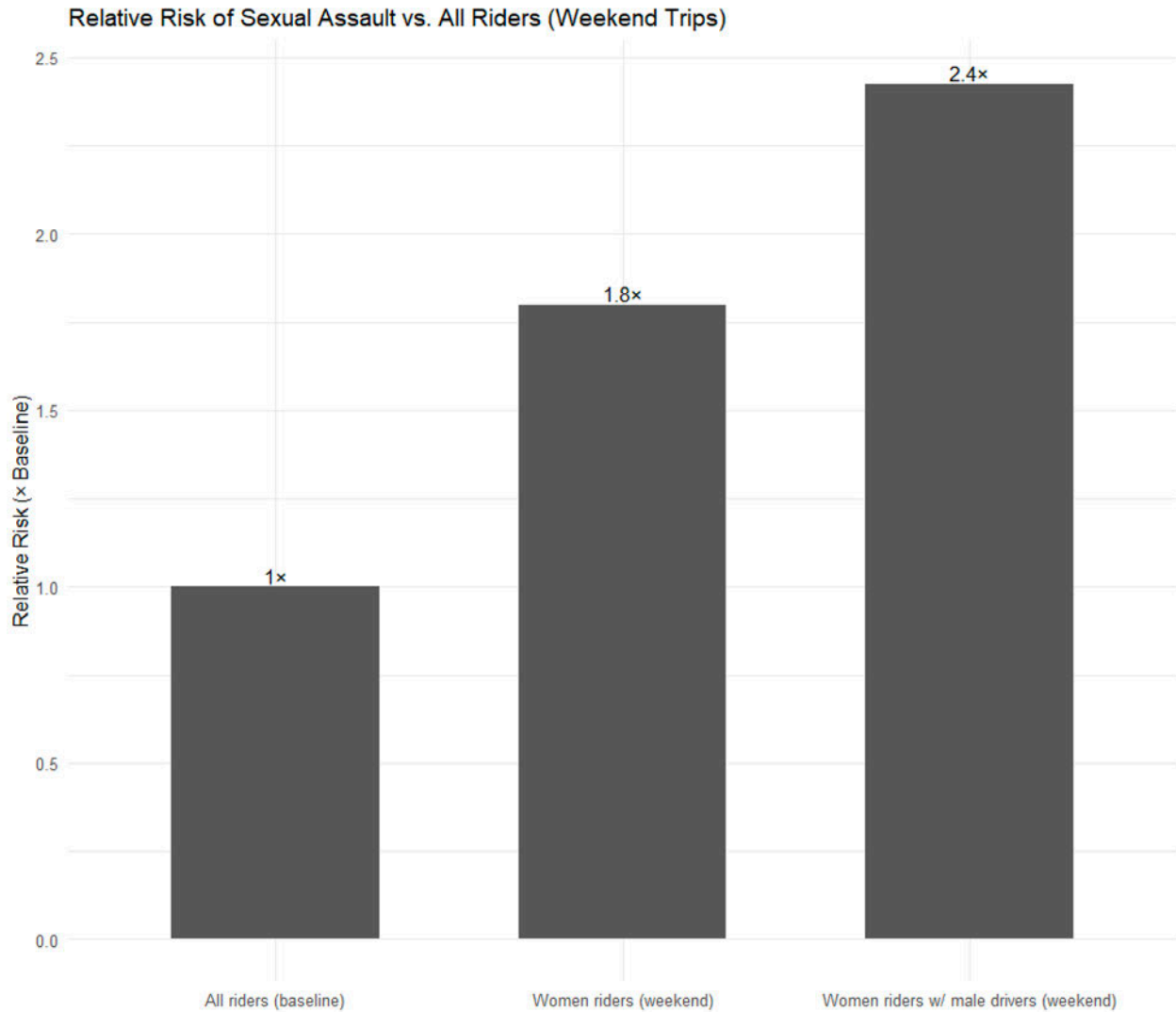
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Figure 3. The relative risk of trip increases as more correlates are added to a particular scenario, as we can see here.

VI. Uber had Access to Data Analysis of the Relative Risk to its Customers on Several Variables

A. Time of Day and Day of Week Patterns

36. Since at least 2017, Uber has had access to data analysis that showed that risk to its passengers was greater at certain times of the day and certain times of the week. A 2017 document analyzing 2016 trends observes that peak counts for rape and sexual assault are between 10:00 p.m. and 4:00 a.m. on Saturday to Sunday.²⁴ The same document also classifies “hour” as the

²⁴ UBER_JCCP_MDL_000031720 at 007. Preventing Sexual Assaults by Sunny Jeon, Emma Pan, Thibault Doutre, and Qi Dong (Feb. 2017).

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variable with the strongest “ability to classify trips with sexual assault vs. trips without sexual assault.”²⁵

37. In a 2017 document that analyzes 2016, Uber notes that [REDACTED]

[REDACTED] In the following table, the

²⁵ UBER_JCCP_MDL_000031720 at 025.

²⁶ Uber’s internal taxonomy historically organized misconduct reports into “levels,” with higher levels indicating more serious or intrusive conduct. In that system, “L3” and “L4” referred to upper-tier Sexual Misconduct categories that included behaviors such as explicit sexual comments, indecent exposure, solicitation of sexual acts, and other conduct more severe than lower-level (L1–L2) complaints.

²⁷ UBER_JCCP_MDL_001741616 at 626. Sexual Misconduct Prevention Plan (Mar. 15, 2017).

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document elaborates on the relative frequencies and statistical significance of sexual misconduct tickets at certain times.²⁸

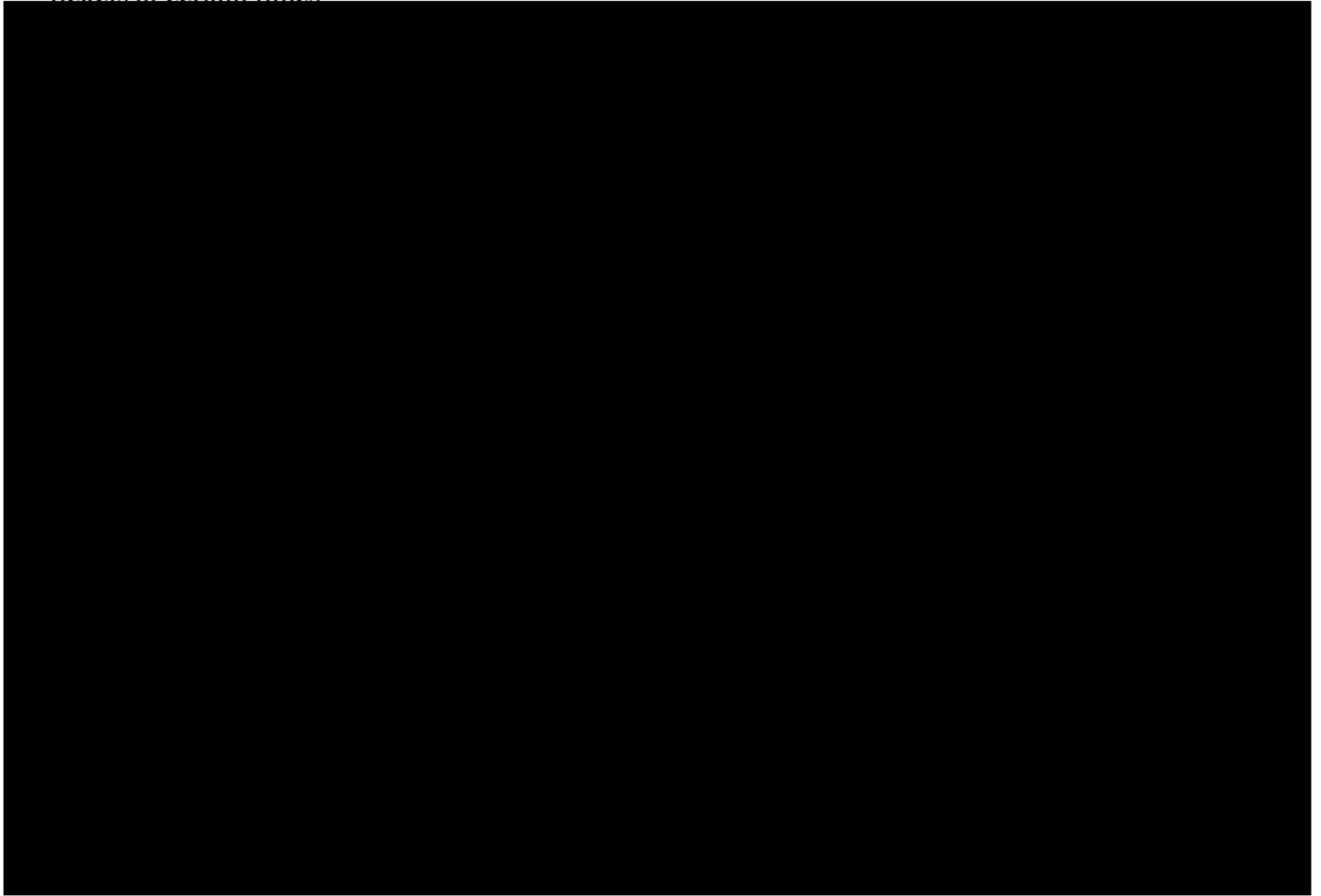
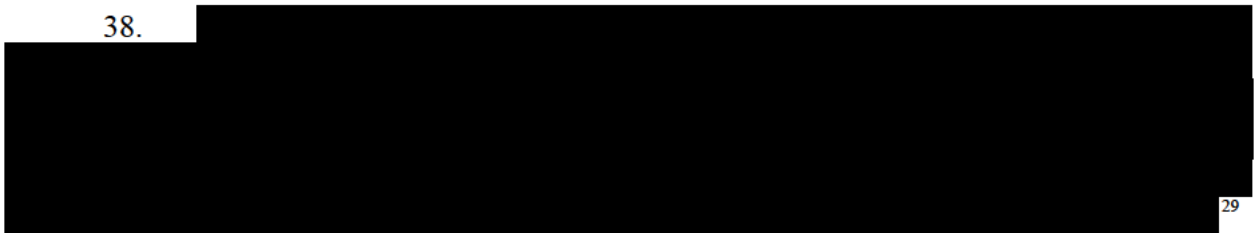


Figure 4.

38.



²⁹

²⁸ UBER_JCCP_MDL_001741616 at 629.

²⁹ UBER_JCCP_MDL_001741616 at 629 and 655-56.

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39. The same document lists the number of sexual offense incidents per day of week and hour of day,³⁰ and the number of incidents per 10M trips by time of day, with the early morning hours containing by far the greatest number.³¹

40. Another 2017 document shows that peak incident rate per 1M trips is on Saturday to Sunday between 10:00 p.m. and 5:00 a.m.³²

41. 2018 documents note similar patterns. Peak incidents for L3 and L4 sexual assault reports per 1M occur on trips between 1:00 a.m. and 3:00 a.m.—this is six times higher than L3 and L4 sexual assault reports per 1M from 4:00 a.m. and 11:00 p.m.³³ Another 2018 document notes that sexual misconduct and sexual assault are disproportionately more likely to occur on late night and weekend trips; it also notes that day and time of week are trip-level predictors of sexual assault.³⁴ This document states in bold that “it may be possible to predict 15% of sexual assaults that occur on Uber platforms by flagging 1% of the highest risk trips.”³⁵ Another 2018 document notes that sexual assaults occur during late night hours, observing similar patterns to previous documents.³⁶

42. Similarly, 2019 documents note time of day and day of week patterns. For instance, Uber observes that [REDACTED] happened between Friday and Sunday.³⁷ Uber also notes that [REDACTED]³⁸ Again, in another document, Uber shows that an increasing number of incidents are observed at night and on weekends, see figure below.³⁹

³⁰ UBER_JCCP_MDL_001741616 at 648.

³¹ UBER_JCCP_MDL_001741616 at 650.

³² UBER_JCCP_MDL_001687315 at 317. Sexual Assaults: Trends + Correlates by Sunny Jeon (July 12, 2017).

³³ UBER_JCCP_MDL_001755017 at slide 13. Personal Safety Deep Dive (June 25, 2018).

³⁴ UBER_JCCP_MDL_003306684 at 685, 691, and 709. S-RAD Model Overview by Sunny Jeon (July 2018).

³⁵ UBER_JCCP_MDL_003306684 at 685.

³⁶ UBER000204698 at 707-709. Safety Trends and Insights (Aug. 8, 2018).

³⁷ UBER_JCCP_MDL_000258366 at 366. Point in Time Messaging (Mar. 11, 2019).

³⁸ UBER_JCCP_MDL_002249692 at slide 17. Safety & Standards Monthly Team Meeting (Aug. 2019).

³⁹ UBER_JCCP_MDL_000250826 at slides 4 and 19. US&C Central Ops Personal Safety (PS) 2020 Opportunity Analysis (Oct. 2019).

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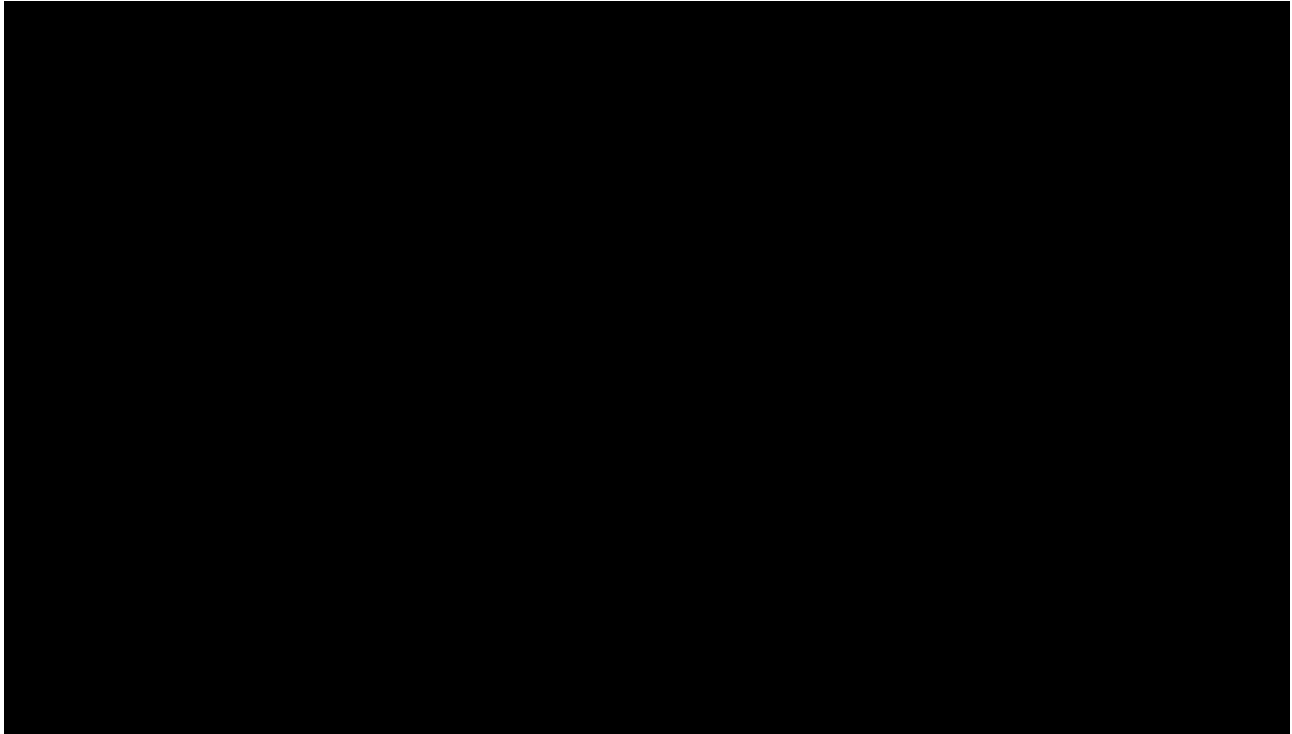


Figure 5. A 2019 risk analysis completed by Uber showing significantly higher risk to platform users on nights and weekends.

43. The pattern persists in 2024, which looks at data from prior years, where Uber notes that evening and weekend trips in the US and Canada are riskier and generate higher serious interpersonal conflict (“IPC” or “SIPC”) rates.⁴⁰

44. Nothing in the new Flack data that I have examined contradicts the conclusions above.

B. Rider and Driver Age Patterns

45. Regarding rider and driver age, Uber also observed patterns in its data regarding sexual assault on its platform. Uber has known since at least 2017 that on average, in cases of sexual assault by drivers, drivers tend to be older than victims. Uber notes that driver age is the variable with the eighth-strongest ability to “classify trips with sexual assault vs. trips without sexual assault.”⁴¹ Uber also observes that sexual misconduct incidents overwhelmingly occur with users between ages twenty and twenty-nine years.⁴² Despite Uber’s knowledge of the role that age plays in estimating the risk of sexual assault, this data is not logged in the Flack data.

⁴⁰ UBER_JCCP_MDL_003504225 at slide 5. Intoxicated Riders by Srishti Bajaj (Apr. 2, 2024).

⁴¹ UBER_JCCP_MDL_000031720 at 025.

⁴² UBER_JCCP_MDL_001741616 at 629 and 655-56.

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46. Uber has had access to data analysis since at least 2017 that shows that being picked up within fifty meters of a bar, as well as being intoxicated to some degree, bear on the risk of sexual assault or misconduct. A 2017 document observes that the number of bars within fifty meters of pickup is a trip-level variable, with the fourth strongest “ability to classify trips with sexual assault vs trips without.”⁴³ The following image depicts one analysis Uber conducted regarding proximity to bars.⁴⁴

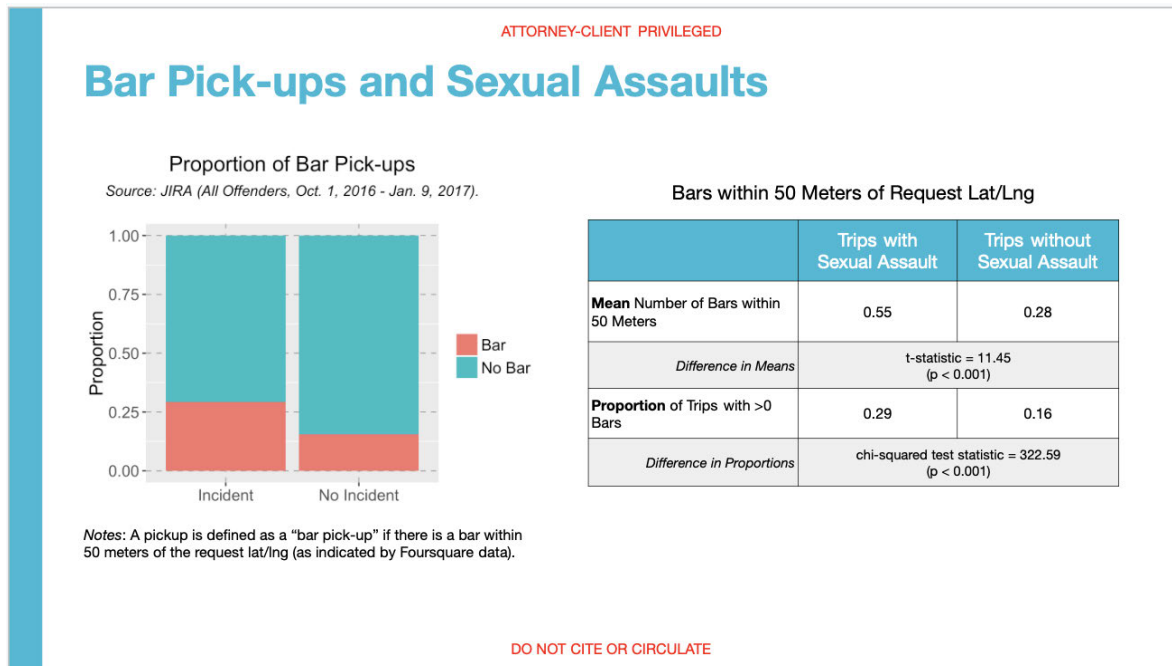


Figure 6. Results from a 2017 risk analysis for pickups requested within 50 meters of a bar.

47. A 2017 document observed that [REDACTED] were visibly disoriented at pickup.⁴⁵ A 2017 document also observed that trips that end in sexual assault are three times more likely to be requested from geohashes where there are greater numbers of bars.⁴⁶

⁴³ UBER_JCCP_MDL_000031720 at 025.

⁴⁴ UBER_JCCP_MDL_000031720 at 009. Note, the Flack data did not have GPS coordinates so I was not able to test this finding.

⁴⁵ UBER_JCCP_MDL_001741616 at 626.

⁴⁶ UBER_JCCP_MDL_001687315 at 320.

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48. In 2018 documents, Uber observed similar patterns. It noted that nearly half of sexual assault reports in the US originated within fifty meters of a bar, and that this location is one of the strongest predictors of sexual assault.⁴⁷

49. In 2019, Uber noted that in an audit of the most serious incidents in the US and Canada, 52% of incidents involved an intoxicated rider.⁴⁸ In 2019 also continued to observe the pattern that the majority of reported sexual assaults originated within fifty meters of a bar.⁴⁹

50. In 2024, Uber observed that nearly half of reported sexual assaults in the US originated within fifty meters of a bar and observed that intoxication remains a risk factor in forty percent of sexual assault and sexual misconduct incidents.⁵⁰

51. Despite Uber's knowledge of the role that alcohol use plays in estimating the risk of sexual assault, this data is not logged in the Flack data.

D. Driver Feedback Patterns

52. Uber has had access to information since at least 2017 that certain kinds of driver feedback are more likely to be strong predictors of sexual assault or sexual misconduct. 2017 documents indicate that Uber had access to data that showed that "creepy driver" feedback is 2.4 times more likely in trips with sexual assault than in trips without,⁵¹ that [REDACTED];⁵² and that trips ending in sexual assault are nearly fifteen times more likely to have a driver who previously received rider feedback containing the word "sex" and four times more likely to have a driver who had previously received rider feedback containing the phrase "inappropriate behavior."⁵³

53. 2018 and 2019 documents show similar patterns. In 2018, Uber documents note that [REDACTED].⁵⁴ In this time period, Uber

⁴⁷ UBER_JCCP_MDL_001755017 at slide 8. Personal Safety Deep Dive (June 25, 2018); UBER_JCCP_MDL_003306684 at 691, 697, and 709; and UBER_JCCP_MDL_002266899 at 906. S-RAD Performance Overview by Sunny Jeon (Nov. 2018).

⁴⁸ UBER_JCCP_MDL_000258366 at 366. Point in Time Messaging (Mar. 11, 2019).

⁴⁹ UBER_JCCP_MDL_002249692 at slide 17; and UBER_JCCP_MDL_000250826 at slide 22.

⁵⁰ UBER_JCCP_MDL_003504225 at slides 4 and 8.

⁵¹ UBER_JCCP_MDL_000031720 slide 17.

⁵² UBER_JCCP_MDL_001741616 at 630.

⁵³ UBER_JCCP_MDL_001687315 at 323. Note, Flack raw data did not include feedback tags, so I was not able to confirm this finding independently.

⁵⁴ UBER_JCCP_MDL_000509298 at 302. Personal Safety H2 Planning (June 12, 2018).

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developed [REDACTED]

[REDACTED] ⁵⁵ A 2019 document makes similar observations and notes that a [REDACTED]

54. Despite Uber's knowledge of the role that patterns in driver feedback plays in estimating the risk of sexual assault, this data is not logged in the Flack data.

E. Patterns in Driver Ratings

55. Uber has had access to information since at least 2015 that indicates that drivers with low ratings (one or two stars) are more likely to sexually assault passengers.⁵⁷

56. 2017 documents observe that [REDACTED]

⁵⁸

57. A 2018 document observes that [REDACTED]

⁵⁹

58. In 2017 Uber also made observations pertaining to lower ratings or two-star ratings that had statistical significance for predicting sexual offenders.⁶⁰

59. The results from a 2017 Uber analysis reports that [REDACTED]

⁵⁵ UBER_JCCP_MDL_003273474 at 493. Analysis of Rider-to-Driver Feedback Tags (US Only) (Nov. 2018); and UBER_JCCP_MDL_000509247 at 017. Safety & Standards Strategy Brief (Oct. 22, 2018).

⁵⁶ UBER_JCCP_MDL_000454790 at 121. US&C ⇔ Safety Product Monthly (May 1, 2019).

⁵⁷ UBER_JCCP_MDL_001687315 at 324. Note, Flack raw data did not include observations on star-ratings, so I was not able to confirm this finding independently.

⁵⁸ UBER_JCCP_MDL_001562549 at 17-21. Sexual Misconduct Policy Revamp Building Blocks by Sytske Besemer (Aug. 23, 2017).

⁵⁹ UBER_JCCP_MDL_000509247 at 013.

⁶⁰ UBER_JCCP_MDL_000031720 at 012; and, UBER_JCCP_MDL_001741616 at 629. Sexual Misconduct Prevention Plan (Mar. 15, 2017).

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61

60. Despite Uber's knowledge of the role that driver ratings plays in estimating the risk of sexual assault, this data is not logged in the Flack data.

F. Patterns in Prior Reports of Sexual Misconduct

61. Uber has had access to information that indicates that sexual assault incidents are more likely with drivers who have previously had a sexual assault complaint.⁶²

62. This pattern is relevant because it speaks to Uber's ability to detect and mitigate elevated-risk situations using its own data. My assignment does not include evaluating Uber's driver-screening or deactivation policies, and I offer no opinions on the adequacy of those systems. But for purposes of understanding the information Uber possessed, the fact that prior sexual-assault complaints are associated with increased subsequent risk demonstrates that Uber had internal markers of heightened danger that could have informed safety interventions. My analysis relies on this only insofar as it shows that Uber had access to data capable of identifying meaningful patterns of risk, including patterns tied to specific drivers.

63. Despite Uber's knowledge of the role that prior reports of sexual misconduct plays in estimating the risk of sexual assault, this data is not logged in the Flack data.

G. Patterns in Prior Reports of Interpersonal Conflict and Aggressive or Dangerous Driving.

64. Similar patterns appear with reports of interpersonal conflict in 2017. Uber had information that showed that one in two-hundred sexual assaults had prior "altercation," and "driver IPC count" is also listed as a variable with the second-strongest ability to "classify trips with SA vs trips without SA."⁶³ Uber also observed that [REDACTED]

. ⁶⁴

65. Similar patterns appear with reports of aggressive or dangerous driving.⁶⁵ Neither patterns of interpersonal conflict nor aggressive driving are logged in the Flack system.

⁶¹ UBER_JCCP_MDL_001741616 at 629 and 655-56.

⁶² UBER_JCCP_MDL_000031720 at slide 12; UBER_JCCP_MDL_001741616 at 630; and, UBER_JCCP_MDL_001687315 at 322.

⁶³ UBER_JCCP_MDL_000031720 at slides 12, 26. Note that Flack raw data did not include observations on reports of aggressive or dangerous driving, or IPC, which prevented me from verifying this finding.

⁶⁴ UBER_JCCP_MDL_001741616 at 630.

⁶⁵ UBER_JCCP_MDL_000031720 at slide 12; and, UBER_JCCP_MDL_001741616 at 630. Again, Flack raw data did not include this information regarding route deviations and pick ups near bars so

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H. Patterns in [REDACTED] and Pick-Ups Near Bars

66. Uber has had information since at least 2017 that [REDACTED].⁶⁶ In internal documents, Uber referred to [REDACTED].⁶⁷

67. Despite Uber's knowledge of the role that [REDACTED] plays in estimating the risk of sexual assault, this data is not logged in the Flack data.

I. Patterns in [REDACTED]

68. Uber has had information that observed patterns in [REDACTED]. A 2017 manual audit observed that [REDACTED].⁶⁸ A 2024 document observed that in the US and Canada, [REDACTED]. A 2017 document also observes tha [REDACTED].⁶⁹

69. Despite Uber's knowledge of the role that patterns of [REDACTED] plays in estimating the risk of sexual assault, this data is not logged in the Flack data.

VII. Relative Risk Analysis for Each of the Five Bellwether Scenarios

70. The preceding analyses establish clear and consistent patterns in Uber's sexual-assault data. Assaults are disproportionately concentrated during late-night hours, especially between midnight and 4 a.m., and the weekend period carries substantially higher per-ride assault risk than weekday periods. This effect is clear when analyzing risk elevation (Section V.A) and absolute risk per ride (Section V.B). These elevated risks are visible both nationally and within the states relevant to the bellwether cases (California, Arizona, and North Carolina). When adjusting for the fact that the overwhelming majority of sexual-assault victims are women and most Uber

even though Uber has documented it since at least 2017, I was not able to verify this independently in my analysis.

⁶⁶ UBER_JCCP_MDL_001741616 at 663.

⁶⁷ UBER_JCCP_MDL_000251111 at 004. Sexual Assault / Misconduct Reduction Strategy (Feb. 17, 2017). Again, Flack raw data did not include this information regarding [REDACTED] so even though Uber has documented it since at least 2017, I was not able to verify this independently in my analysis.

⁶⁸ UBER_JCCP_MDL_001741616 at 663.

⁶⁹ UBER_JCCP_MDL_001562549 at slide 21.

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drivers are men, the risks to women taking Uber rides during weekend and late night periods become even more pronounced.

71. The five bellwether incidents fall naturally into this framework. Because Uber did not produce the trip-level variables it uses in its own S-RAD system, it is not possible to compute a formal, stand-alone statistical estimate of relative risk for any single bellwether ride. Had Uber provided the same data it relies on internally, I could have calculated trip-specific relative risks in the same manner. In the absence of those inputs, each incident is instead evaluated against the empirically established population-level patterns identified in Section V. This provides meaningful context: each bellwether plaintiff's ride can be assessed in terms of whether it occurred during one of the high-risk portions of the week, in a state where weekend or late-night risks are elevated, and under conditions (such as a male driver and a female rider) that increase the likelihood of assault. In the subsections that follow, I briefly describe each bellwether incident in this context.

A. Jaylynn Dean: November 15, 2023 (12:33 AM, Tempe)

72. This trip occurred at 12:33 a.m. on a midweek night. While not a weekend ride, it nevertheless falls within the highest-risk four-hour window identified across Uber's data. Section V.A shows that the severity profile of incidents shifts sharply during this period, with a disproportionate share of penetrative sexual assaults occurring between midnight and 4 a.m. The plaintiff's experience matches this pattern.

73. Although Arizona's weekend risk is higher overall, the late-night escalation pattern operates independently of day-of-week: a ride at 12:33 a.m. carries greater risk than the same ride taken during daytime hours. As with the other bellwether cases, the combination of a female rider and a male driver further increases the underlying risk relative to the baseline rate for all riders.

B. [REDACTED]: August 12, 2022 (3:53 AM, San Francisco)

74. This trip occurred at 3:53 a.m., squarely within the midnight–4 a.m. time of day period that exhibits the highest concentration of sexual assaults on Uber's platform. As shown in Section V.A, the likelihood that a sexual incident escalates to a sexual assault rather than misconduct peaks during these hours.

75. Because the victim is a woman and the assailant a male driver, the gender-adjusted per-ride risk faced by the plaintiff during this trip was substantially greater than the baseline rate for all riders. In short, this incident occurred during one of the more dangerous portions of the week for women using Uber.

C. [REDACTED]: March 26, 2019 (1:25 AM, Raleigh)

76. This trip took place at 1:25 a.m., firmly within the late-night high-risk window identified in my analyses. North Carolina shows the same escalation pattern as the national data: sexual assaults cluster heavily in the early-morning hours, even on weekdays, and the relative likelihood of sexual assault versus sexual misconduct increases sharply at these times.

77. While weekend rides in North Carolina carry the highest per-ride assault risk, the late-night period represents the most dangerous time of day for women using Uber. Given the

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timing of this ride and the plaintiff's pairing with a male driver, the conditions of this incident closely match the elevated-risk patterns Uber's data reveal.

D. [REDACTED] June 28, 2024 (10:23 PM, Phoenix)

78. This ride occurred at 10:23 p.m. on a Friday night, during the period when risk begins rising toward the late-night peak documented in the escalation heatmap. Although not yet past midnight, Friday evenings show a marked increase in both the rate and severity of sexual assaults on Uber's platform.

79. Arizona mirrors the national pattern, with weekend per-ride sexual-assault risk clearly exceeding weekday risk. For women matched with male drivers—a large majority of Uber trips—the adjusted weekend risk is several times the baseline rate for all riders. The timing and circumstances of this Arizona bellwether incident therefore align closely with the elevated-risk conditions identified in Section V.

E. [REDACTED]: August 10, 2023 (12:41 AM, San Francisco)

80. Although this ride occurred on a Thursday night, not a weekend, it occurred at 12:41 a.m., inside the same late-night window in which sexual-assault risk sharply increases. As demonstrated in Section V.A, even outside weekends, sexual assaults occur disproportionately during the early-morning hours, and the severity mix shifts toward more serious forms of assault. This incident followed precisely that pattern.

81. California's annual data continue to show elevated weekend risk, but the underlying escalation pattern makes clear that late-night rides—regardless of day of week—carry higher risk than daytime rides. Because the plaintiff is a woman and was paired with a male driver, the baseline risk for this trip is amplified under the gender-adjusted model described above.

VIII. Uber Documents Show Uber had Relative Risk Variables for Each of the Five Bellwether Scenarios**A. Jaylynn Dean**

82. Plaintiff Jaylynn Dean, a 19-year-old female, alleges that she was raped by her Uber driver, Hussan Turay, a male in his 40s on Wednesday, November 15, 2023, after requesting a ride from an apartment in Tempe, AZ to a hotel.⁷⁰ Ms. Dean's trip began at 12:33 AM.⁷¹ Ms. Dean was

⁷⁰ BW-DEAN_JAYLYNN_000026. Tempe Police Dept. General Offense Report # TE 2023-132207; UBER-MDL3084-DFS00003727. Uber Report on Jaylynn Dean's Incident [SAFE-4071034]; and, UBER-MDL3084-BW-00027901. Uber App trip receipt for Jaylynn Dean's trip.

⁷¹ UBER-MDL3084-DFS00003727.

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intoxicated at the time of her trip.⁷² The address of her pickup location (2210 N Scottsdale Rd., Tempe, AZ 85281) is the site of a restaurant and bar.⁷³

83. Additionally, prior to the incident trip, Uber had the following information about Ms. Dean's driver:

- 24 trips with off-route/route deviation indicators;
- 119 trips with long stop indicators;
- 95 trips that ended midway or at a location other than the destination;
- 2 prior reports of SA/SM;
- 62 trips with 1-star ratings; and
- 12 trips with 2-star ratings.⁷⁴

84. Ms. Dean's driver had received the following feedback tags where the rating was less than 5 stars:

- 10 tags for "professionalism;"
- 3 tags for "comfort;"
- 3 tags for "conversation;" and
- 7 tags for "driver not polite."⁷⁵

85. Ms. Dean's driver had also received:

- 20 feedback tags associated with unsafe or dangerous driving (with a less than 5-star rating).⁷⁶

86. Ms. Dean's driver had a preference for late-night trips.⁷⁷

⁷² BW-DEAN_JAYLYNN_000026.

⁷³ Mapquest. Business at 2210 N. Scottsdale Rd., Tempe, AZ 85281. Accessed Nov. 29, 2025. <https://www.mapquest.com/us/arizona/zu-izakaya-369010804>.

⁷⁴ UBER-MDL3084-BW-00049300. Driver Hassan Turay trip GPS event log; UBER-MDL3084-BW-00048883. Driver Hassan Turay Ride Check (12-07-2016 to 06-30-2025); UBER-MDL3084-DFS00159600. Driver Hassan Turay Incident History; and UBER-MDL3084-BW-000050792. Driver Hassan Turay Feedback.

⁷⁵ UBER-MDL3084-BW-000050792.

⁷⁶ UBER-MDL3084-BW-000050792.

⁷⁷ UBER-MDL3084-DFS00159678. Uber and Hassan recorded call; and, UBERMDL3084-DFS00159672. Bliss Phone Transcript c162cbcf-196f-4cf5-87ab-abe1cdb4f12c (Hassan is "[u]sually is up at night and sleeping during the day.").

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87. Ms. Dean's driver had received numerous monetary appeasements from Uber for cleaning, which can indicate a rider vomiting in the vehicle. On September 4, 2023 (approximately 2 months before the incident trip), Uber informed the driver that Uber had "noticed [he had] recently received a high number of cleaning fees."⁷⁸

88. Ms. Dean's driver had a history of cancelling trips that were outside of his preferences.⁷⁹

89. In light of my review of the information and the analysis that Uber possessed to predict elevated risk, my analysis of the Flack raw data, and my observations here of the circumstances surrounding Ms. Dean's ride, including driver behavior, driver feedback, and time and location of ride, I can now say with a reasonable degree of scientific certainty that Uber had access to information that would allow the company to predict high risk patterns for Ms. Dean's ride on the night she reported an assault.

B.

90. Plaintiff [REDACTED] was a 34-year-old female at the time she alleges that she was raped by her Uber driver, Edwin Castaneda Orozco, a 44-year-old male on Friday, August 12, 2022, after requesting an Uber ride from her aunt's house in San Jose, California to her brother's apartment in Campbell, California.⁸⁰ Ms. [REDACTED]'s trip began at 3:53 AM.⁸¹

91. Ms. [REDACTED] was intoxicated at the time of her trip.⁸²

92. Additionally, prior to the incident trip, Uber was aware of the following information about Ms. [REDACTED] driver:

- 1 trip with a long stop indicator;
- 4 trips that ended midway or at a location other than the destination;
- 4 trips in which GPS tracking showed the driver lingering at the rider's destination; and

⁷⁸ UBER-MDL3084-BW-00008573. Hassan requested cleaning for vomit in the vehicle (Sept. 4, 2023).

⁷⁹ UBER-MDL3084-BW-00008486. Uber Support chat requested by Hussan Turay Title: Tracking Acceptance and Cancellation Rates (Aug. 3, 2023).

⁸⁰ UBER-MDL3084-BW-00028166. Uber App trip receipt for [REDACTED] trip; and, UBER-MDL3084-BW-00028164. CA Driver License for Edwin Castaneda Orozco.

⁸¹ UBER-MDL3084-BW-00028166.

⁸² Dep. [REDACTED] June 25, 2025 at 158:15-16 ("I had also drank 10 shots of vodka that night. I had had Truly's.").

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- 2 trips with 2-star ratings, and one of these was seven days before his incident with Ms. [REDACTED].⁸³

93. Additionally, Ms. [REDACTED] driver had received the following feedback tags:

- 1 tag for “professionalism” less than a month before his incident with Ms. [REDACTED].⁸⁴

94. One report from July 13, 2022, a month prior to the incident ride, reported dangerous driving activity by the driver.⁸⁵

95. In light of my review of the information and the analysis that Uber possessed to predict elevated risk, my analysis of the Flack raw data, and my observations here of the circumstances surrounding Ms. [REDACTED] ride, including driver behavior, driver feedback, passenger intoxication, and time of ride, I can now say with a reasonable degree of scientific certainty that Uber had access to information that would allow the company to predict high risk patterns for Ms. [REDACTED] ride on the night she reported an assault.

C. [REDACTED]

96. Plaintiff [REDACTED] was a 23-year-old female at the time she alleges that she was sexually assaulted by her male Uber driver, Jeffery Richardson, on Tuesday, March 26, 2019 after requesting an Uber ride in Raleigh, North Carolina from her friend’s home to another residence.⁸⁶ Ms. [REDACTED] trip began at 1:25 AM.⁸⁷ Ms. [REDACTED] Uber driver requested that she sit in the front seat, and she complied.⁸⁸

⁸³ UBER-MDL3084-BW-0049301. Driver Edwin Castaneda Orozco trip GPS event log; and, UBER-MDL3084-BW-00050793. Driver Edwin Castaneda Orozco Feedback.

⁸⁴ UBER-MDL3084-BW-00050793.

⁸⁵ UBER-MDL3084-BW-00049313. Uber Support chat Title: Review my cancellation fee (July 13, 2022); and UBER-MDL3084-BW-00049317. Uber Support chat Title: Rider Discovery Bot Get Trip Help (July 13, 2022). Although the report should have been classified as dangerous driving, the support agent handling the incident report misclassified it. *See also*, Greg Brown Dep. Aug. 26, 2025 at 395:24-398:13; referencing: UBER-MDL3084-DFS00015927.

⁸⁶ UBER-MDL3084-BW-00048509. Uber App trip receipt for [REDACTED] trip; and [REDACTED] CO-000018. Behavioral Health Urgent Care Note (Feb. 7, 2022).

⁸⁷ UBER-MDL3084-BW-00048509.

⁸⁸ Dep. B.M. July 10, 2025 at 33:2-11 (“Q: what do you recall about your Uber ride home from Mr. Woodham’s house in the early morning of March 26, 2019? A. I remember when he came to the house, I was going to get in the back seat, and he offered for me to sit in the front for whatever reason. And I figured he just didn’t want to chauffeur me. I don’t know exactly what was going through his head, but I thought nothing of it and sat in the front seat.”).

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97. Additionally, in the prior four months to the incident trip, Uber was aware of the following information about Ms. [REDACTED] driver:

- 6 trips with 1-star ratings.⁸⁹

98. Ms. [REDACTED] driver had a preference for late-night trips.⁹⁰

99. In light of my review of the information and the analysis that Uber possessed to predict elevated risk, my analysis of the Flack raw data and my observations here of the circumstances surrounding Ms. [REDACTED] ride, including driver behavior, driver feedback, and time of ride, I can now say with a reasonable degree of scientific certainty that Uber had access to information that would allow the company to predict high risk patterns for Ms. Mensing's ride on the night she reported an assault.

D.

100. Plaintiff [REDACTED] was 30 years old on the night she alleges that her Uber driver, Felix Perez Rodriguez, non-consensually touched a sexual body part on Friday, June 28, 2024, after requesting an Uber ride in Tempe, AZ.⁹¹ Ms. [REDACTED] trip began at 10:23 PM.⁹² Her trip request was made from within 50m of a bar.⁹³ The driver asked Ms. [REDACTED] to sit in the front seat because of her bags, and she complied.⁹⁴

101. Additionally, prior to the incident trip, Uber was aware of the following information about Ms. [REDACTED] driver:

- 1 prior reports of SA/SM;
- 160 trips with 1-star ratings; and

⁸⁹ UBER-MDL3084-BW-00050795. Driver Jeffery Richardson Feedback.

⁹⁰ Dep. Greg Brown, Aug. 26, 2025 at 339:23-340:6 ("Q. At the risk of boring us to death, this pattern -- and feel free to scroll through it in Box or however you want, this continues throughout his entire time with Uber, that he drives, it appears, exclusively at almost exclusively in the evenings and early mornings. Do you see that? A. Yeah, I see that pattern based on the ones -- the days we have reviewed here, yes."); and, UBERMDL3084-BW-00050795.

⁹¹ Am. Pl. Fact Sheet, MDL No. 3084 CRB for Case No. 24-cv-07019, [REDACTED]. ("LCHB128 Fact Sheet")

⁹² LCHB128 Fact Sheet.

⁹³ Dep. of Greg Brown, Aug. 25, 2025 at 167:4-7 ("Q. And the pickup location was a plaza in Tempe, Arizona, that had bars and restaurants around it, right? A. Yes, that sounds right.").

⁹⁴ LCHB128 Fact Sheet.

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- 60 trips with 2-star ratings.⁹⁵

102. Ms. [REDACTED] driver had also received 14 reports of unsafe or dangerous driving.⁹⁶

103. In light of my review of the information and the analysis that Uber possessed to predict elevated risk, my analysis of the Flack raw data, and my observations here of the circumstances surrounding Ms. [REDACTED] ride, including driver behavior, driver feedback, and time and location of ride, I can now say with a reasonable degree of scientific certainty that Uber had access to information that would allow the company to predict high risk patterns for Ms. Minfield's ride on the night she reported an assault.

E. [REDACTED]

104. Plaintiff [REDACTED] was 27 years old on the night she alleges that she was sexually assaulted by her Uber driver, Michael Le, a male on Thursday, August 10, 2023, after requesting an Uber ride from a charity event to her home in San Francisco.⁹⁷ Ms. [REDACTED] requested her trip at 12:36 AM.⁹⁸ Her trip request was made from within 50m of a bar and Ms. [REDACTED] was intoxicated at the time of her trip.⁹⁹ Ms. [REDACTED] driver requested that Ms. [REDACTED] sit in the front seat, and she complied.¹⁰⁰

⁹⁵ UBER-MDL3084-DFS00159622. Driver Felix Perez Rodriguez Incident History; and, UBER-MDL3084-BW-000050791. Driver Felix Perez Rodriguez Feedback.

⁹⁶ UBER-MDL3084-DFS00159622.

⁹⁷ UBER-MDL3084-DFS00160119. Trip Chronicle for trip 672ad6de-61bb-44d6-9c78-25d1c3a0ba15; and, Am. Pl. Fact Sheet, MDL No. 3084 CRB for Case No. 24-cv-07821, [REDACTED]. ("A.R. Fact Sheet")

⁹⁸ UBER-MDL3084-DFS00054848. Trip Chronicle for trip 672ad6de-61bb-44d6-9c78-25d1c3a0ba15.

⁹⁹ UBER-MDL3084-DFS00160119; UBER-MDL3038-BW-00048905. SRAD Data for trip 672ad6de-61bb-44d6-9c78-25d1c3a0ba15; [REDACTED] Dep. July 1, 2025 at 72:15-19 ("Q. When you left the Italian Athletic Club on August 9th at around 12:40 in the morning, did you still feel the wine that you had had? A. I felt slightly tipsy.").

¹⁰⁰ A.R. Fact Sheet; and, [REDACTED] Dep. at 71:4-25 ("Q. What happened as you got into the car? A. I first walked around the back of the car to check the license plate to make sure it was my Uber. And then when I was getting into the back of the car, the Uber driver asked me if I wanted to sit in the front seat and I said yes. He said it would probably be more comfortable. It's not unusual for me to want to sit in the front seat. I get carsick frequently, and I'm quite tall, so often will ask to sit in the front seat. Q. Were the back seats of the car obstructed? A. No. Q. They didn't have anything in them? A. No. Q. Do you recall whether you asked to sit in the front seat that night? A. He asked me if I wanted to sit in the front seat. So yes, I recall that I did not ask to sit in the front seat.").

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105. Additionally, prior to the incident trip, Uber was aware of the following information about Ms. [REDACTED] driver:

- 3 trips with off-route/route deviation indicators;
- 11 trips with long stop indicators;
- 39 trips that ended midway or at a location other than the destination;
- 1 prior report of SA/SM marked insufficient info by Uber;
- 12 trips with 1-star ratings; and
- 2 trips with 2-star ratings.¹⁰¹

106. Ms. [REDACTED] driver had received the following feedback tags:

- 3 tags for “not polite.”¹⁰²

107. One report from June 18, 2023, around two months prior to Mr. Le and Ms. [REDACTED] incident, contains very little data, but the Uber user reported Mr. Le’s vehicle as unsafe.¹⁰³ Uber Global Safety Support categorized this report as sexual misconduct and where the user was asked, “[w]hy did the vehicle feel unsafe,” the user comments are short and concise and simply state, “rapist.”¹⁰⁴

108. In light of my review of the information and the analysis that Uber possessed to predict elevated risk, my analysis of the Flack raw data, and my observations here of the circumstances surrounding Ms. [REDACTED] ride, including driver behavior, driver feedback, and time of ride, location of ride, and intoxication, I can now say with a reasonable degree of scientific certainty that Uber had access to information that would allow the company to predict high risk patterns for Ms. [REDACTED] ride on the night she reported an assault.

IX. The Flack Data Reveal that Uber Underreported the True Number of Incidents

109. In my Opening Report, I used data from the National Crime Victimization Survey (NCVS) and a hierarchical model to estimate how many sexual assaults actually occurred on Uber’s platform, recognizing that only a fraction are ever reported. That analysis was necessarily conducted at a higher level of aggregation due to the limitations of the previous production available at the time of my Opening Report, and that analysis could not distinguish incidents by assailant type. With the Flack raw data, I can now repeat that analysis using a much more precise

¹⁰¹ UBER-MDL3084-BW-00049302. Driver Michael Le trip GPS event log; UBER-MDL3084-DFS00159626. Driver Michael Le Incident History; and, UBER-MDL3084-BW-00050794. Driver Michael Le Feedback.

¹⁰² UBER-MDL3084-BW-00050794.

¹⁰³ UBER-MDL3084-DFS00054771. June 18, 2023 In-app Report Chat from an Uber user identified only as Ming.

¹⁰⁴ UBER-MDL3084-DFS00054771.

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subset of incidents: those in which Uber’s own incident-classification process identifies the driver as the alleged assailant. This allows me to estimate the true number of driver-initiated sexual assaults, rather than all sexual incidents taken together.

110. For this analysis, I used the same NCVS-based framework as in my opening report. The NCVS reports the proportion of sexual assaults that victims say they reported to the police in each year, and my earlier model converted those proportions and their margins of error into a set of Beta distribution parameters by year. These distributions serve as priors on the probability that a given sexual assault is reported. In the updated Flack model, I apply the same priors but restrict the incident data to Flack records coded as sexual assault or sexual misconduct in Uber’s official taxonomy, where the alleged assailant is the driver. I aggregate those incident counts to the annual level by incident type and year and use the same ride-volume data as in my opening report to provide the exposure term (rides) for each year.

111. The Flack data represent incidents reported to Uber, not the true universe of events on the platform. To account for the fact that some small fraction of incoming reports may reflect misclassification or support abuse rather than a true sexual assault, I apply a simple, conservative adjustment before fitting the model: I reduce each annual driver-assailant incident count by 4.5%.¹⁰⁵ Empirical studies of false reporting rates for sexual assault suggest that such cases are rare, and there is no evidence that Uber’s system is uniquely prone to over-reporting. Treating 4.5% of the Flack incidents as potential non-events therefore errs on the side of caution and reduces the resulting estimates of true assaults.

112. I then fit the same hierarchical negative-binomial model I used in my opening report. The model simultaneously estimates (1) the underlying rate at which driver-initiated sexual assaults occur per ride, (2) annual effects that allow reporting rates to vary by year, and (3) incident-type effects that allow for differences in how likely various forms of assault and misconduct are to be reported. The NCVS-based priors anchor the model using independent information about how rarely sexual assaults are reported to the police, while the Flack counts and ride volumes update those priors to reflect Uber’s data.

113. In the baseline NCVS scenario, I set the prior probability that a sexual assault or misconduct incident is reported to Uber based on the rate that such incidents are reported to the police, the model implies a median reporting probability of approximately 29% across the Flack period. This means that Uber’s internal systems capture only about 1 in 3.5 driver-initiated sexual assaults that actually occur on the platform. Put differently, for every driver-assailant incident that appears in the Flack data, the model estimates roughly 3.5 such assaults in reality. Over the 2017–2024 period, the posterior median estimate of the total number of driver-initiated sexual assaults or misconducts is about 1.30 million incidents, with a 95% credible interval from roughly 1.10 million to 1.58 million. There are 392 thousand such incidents reported in Flack and my estimates are higher by this same factor of 3.5, even after thinning the reported incidents by 4.5 percent to allow for potential support-abuse cases.

¹⁰⁵ Spohn C., White C., Tellis K. (2014) “Unfounding Sexual Assault: Examining the Decision to Unfound and Identifying False Reports.” *Law & Society Review*, vol. 48, no. 1:161-192. doi:10.1111/lasr.12060

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114. In my deposition it was suggested that riders might be more willing to report sexual assaults and misconducts to Uber than to the police, thus, I also estimated a second scenario more favorable to Uber. Under this assumption, riders are treated as if they were substantially more likely to report incidents to Uber than to law enforcement. This is not a claim about how riders actually behave; it is a way of exploring how much the results would change under assumptions that are more favorable to Uber. Under this “higher Uber reporting” scenario, the model yields a median reporting probability of 44%, reducing the degree of inferred under-reporting. Even under this more optimistic assumption, however, the posterior median still indicates that Uber is capturing only about 1 in 2.3 driver-initiated sexual assaults and misconducts. The corresponding total-incident estimate over 2017–2024 remains well above the raw Flack counts, at approximately 859 thousand driver-initiated sexual assaults and misconducts, with a 95% credible interval from 734 thousand to 1.02 million incidents—still well above the raw counts in Flack.

115. Finally, I estimated a scenario in which riders are assumed to be less likely to report incidents to Uber than to police, by decreasing the NCVS reporting priors by 50 percent. This produces a median reporting probability of only 14%, implying substantially greater under-reporting to Uber. Under this assumption, Uber’s internal data would be capturing only about 1 in 7 driver-initiated sexual assaults and misconducts. The posterior median estimate of total incidents rises accordingly, to approximately 2.63 million over 2017–2024, with a 95% credible interval from 2.10 million to 3.38 million. This scenario is not intended as a claim about true rider behavior; it illustrates the degree to which Uber’s measured data could understate the true number of incidents if riders report less frequently to the platform than to law enforcement.

116. These estimates are conservative in several ways. First, they apply a downward adjustment to the Flack counts to reflect the possibility of support abuse, even though there is no evidence that more than a small fraction of Flack incidents falls into that category. Second, they are restricted to incidents where Uber’s classification logic identifies the driver as the alleged assailant. Assaults committed by riders or third parties are excluded from these counts; incorporating those additional incidents would increase the total number of sexual assaults occurring on the platform. Third, the sensitivity analysis assumes that riders are substantially more willing to report sexual assaults and misconducts to Uber than to the police, an assumption that is at odds with several features of the ride-sharing environment that tend to depress reporting to Uber, such as the driver’s knowledge of the rider’s home address, fear of retaliation, intoxication during late-night trips, and uncertainty about whether Uber is the appropriate entity to contact. Even under these favorable assumptions, Uber’s internal Flack data reflect only a fraction of the driver-initiated sexual assaults that likely occurred.

117. In sum, re-fitting my under-reporting model using the Flack driver-assailant data confirms and strengthens the conclusions from my opening report. Uber’s own records, even after conservative thinning and even under assumptions that make reporting to Uber appear easier than reporting to the police, imply that the true number of driver-initiated sexual assaults and misconducts on the platform is several times larger than the number of incidents Uber has recorded. The five bellwether incidents should therefore be understood not as isolated aberrations, but as examples drawn from a much larger set of assaults that Uber’s systems only partially capture.

HIGHLY CONFIDENTIAL**X. The Flack Data Reveals Increasing Incident Rates from 2023-2024**

118. Using the newly produced Flack data, I estimated the true monthly incidence of sexual assault and sexual misconduct from 2021 through 2024. The raw monthly counts show month-to-month variation, but because most sexual assaults are never reported, I use the Bayesian under-reporting model described above to estimate the true number of incidents. I distribute the annual posterior estimates across months in proportion to Uber's observed monthly patterns, which preserves seasonality while correcting for under-reporting. For consistency with the bellwether period, Figure X displays monthly estimates only through June 2024, even though the underlying model is fit to data through the end of 2024. The results are seen in the next figure.

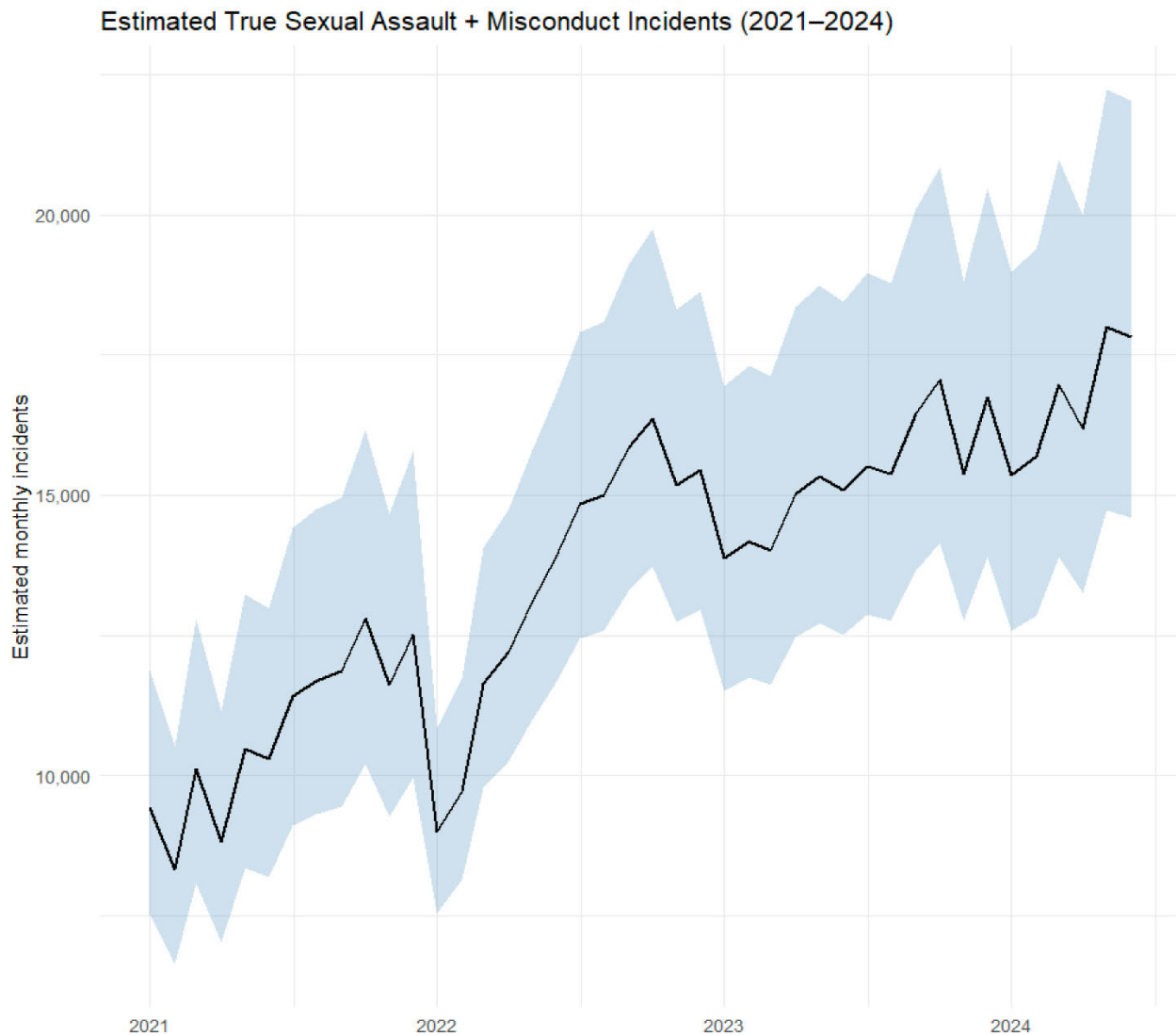


Figure 7. Estimated true number of sexual assault and sexual misconduct on Uber's platform calculated using the most recently released incident data by Uber.

119. The results show a rising trend in true driver-assailant incidents over 2023 and the first half of 2024. By the end of 2024, the level of incidents has dropped back to early 2023 levels. This contrasts with Uber's last published Safety Report, which claimed declining rates. The trend

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is particularly notable because Uber has chosen not to release any 2023–2024 Safety Report despite already having the underlying data. Note that, while all the Safety Reports acknowledge underreporting, none of them accounts for it.

120. I calculated annual incident rates by dividing the total number of Flack sexual-safety incidents in each year by the number of rides in that year, and scaling the result to incidents per 100 million trips. These rates fall sharply in 2020–2021, when the COVID-19 pandemic dramatically reduced overall ridership, but then begin rising again. Between 2022 and 2023, the overall incident rate increased from approximately 4,723 to 5,096 incidents per 100 million trips, and it rose again between 2023 and 2024, from 5,096 to 5,482. In other words, once the COVID-period anomaly is set aside, Uber’s own data show that sexual-safety incidents per trip have been trending upward in the most recent years. These rates can be seen in the following chart.

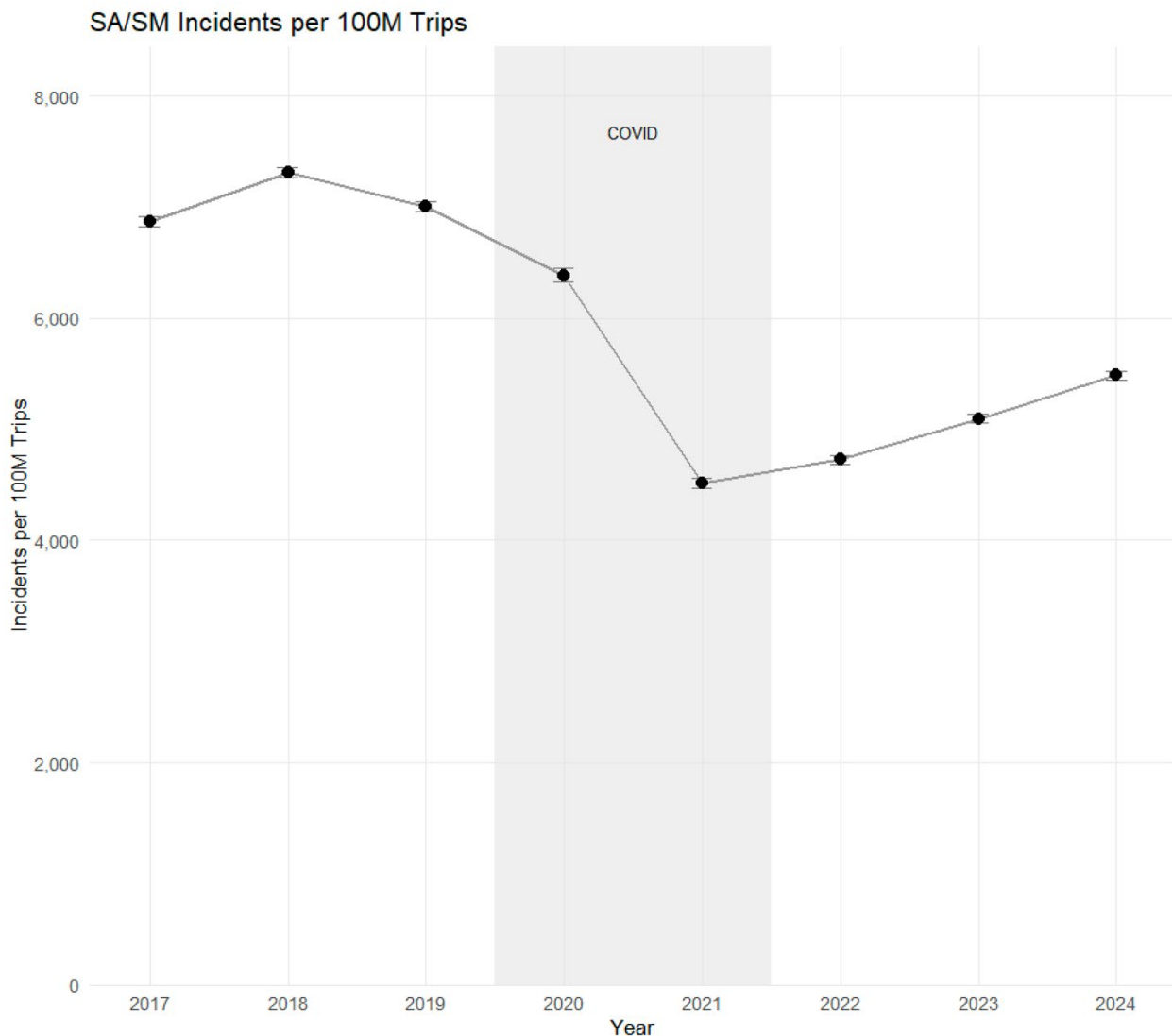
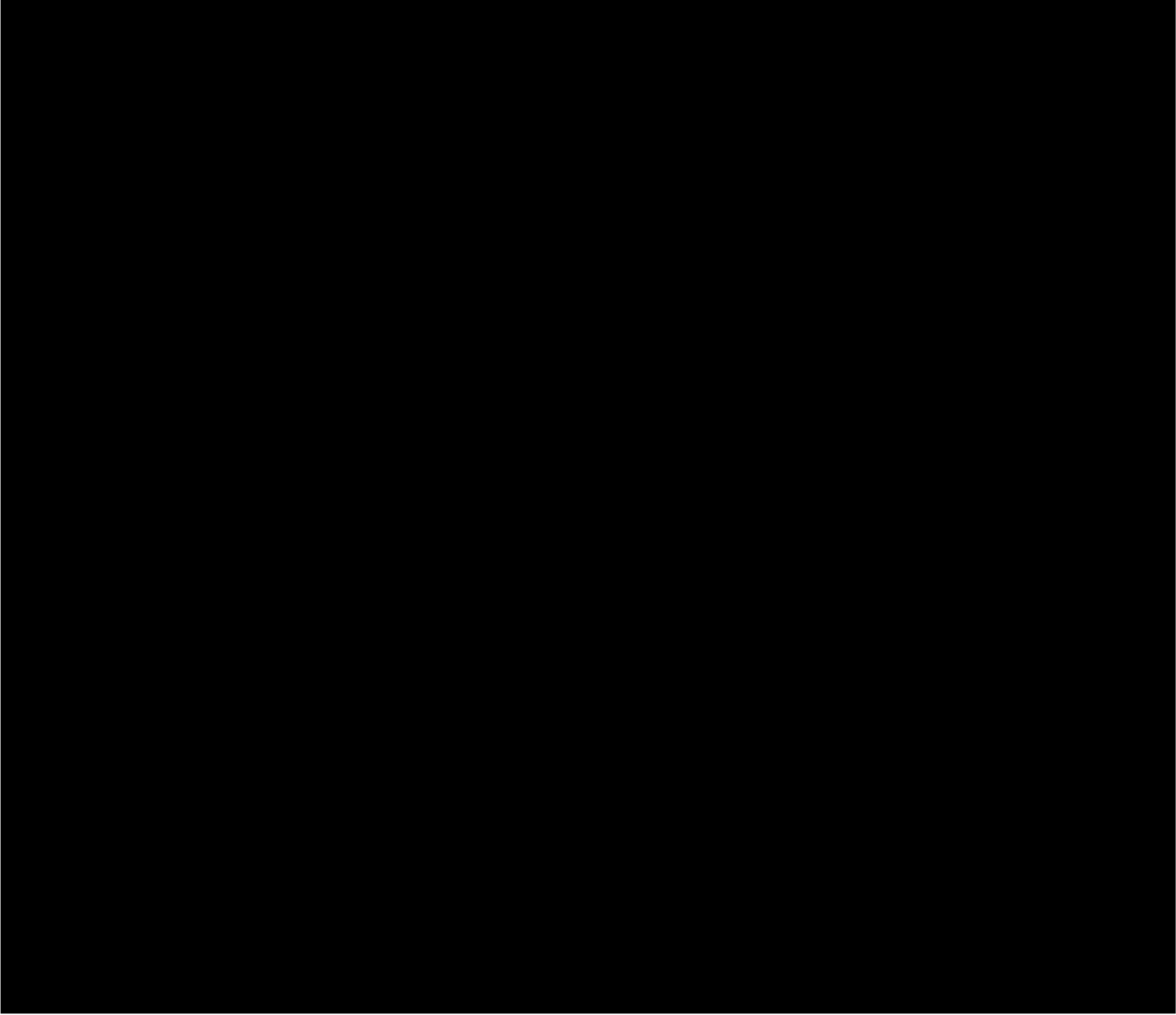


Figure 8: SA/SM rates per 100M trips by year from 2017 through 2024. Poisson uncertainty intervals added.

121. I performed the same calculation focusing specifically on rape incidents—reports coded in Flack as non-consensual sexual penetration. In 2017, the rape incident rate was

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approximately [REDACTED], and in 2023 it was essentially the same, at about [REDACTED]. By 2024, the rape rate had risen slightly further, to about [REDACTED]. Uber's own data do not show any sustained reduction in the per-ride risk of rape. Indeed, by 2024 the rape rate is at its highest level in the series.



122. To formally assess whether the per-ride incident rates differ across years, I conduct Poisson rate-ratio tests, which are standard for comparing event rates observed over different exposure levels (here, the number of Uber rides in each year). The method treats the number of reported incidents in each year as arising from a Poisson process with a rate proportional to ride volume, and it tests the null hypothesis that the two years share the same underlying incident rate. The resulting rate ratio quantifies how much higher (or lower) one year's rate is relative to the other. A rate ratio of 1 means the years have the same rate; values above or below 1 indicate higher or lower rates, respectively. These tests provide a clear way to evaluate whether the changes are statistically meaningful or simply reflect random fluctuation.

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123. The results can be seen in the following table. The ratios, all below 1.0, indicate that each of these rates were higher in the second year than in the first, though not all of the differences are statistically significant:

Rate Type	Year Comparison	Year Rate ¹⁰⁶	1 Year 2 Rate	Ratio	P-Value
SA/SM	2022 vs 2023	4,723	5,096	0.927	$p < 10^{-10}$
SA/SM	2023 vs 2024	5,096	5,482	0.93	$p < 10^{-10}$
████	████	████	████	████	████
████	████	████	████	████	████
████	████	████	████	████	████

XI. Repeated Exposure Analysis

124. Riders typically take about 5–6 trips per month in the US, for a total of 60–70 trips per year.¹⁰⁷ Plaintiffs trip counts were determined using the communication logs provided and are as follow: Jaylynn Dean, 5 trips¹⁰⁸; ██████████ 23 trips¹⁰⁹; ██████████, 2 trips¹¹⁰; ██████████ 484 trips¹¹¹; and ██████████, 1,214 trips¹¹². Each one of those trips carries a small but non-zero risk of sexual assault. For repeat riders, the cumulative risk across all the trips they take in a year is a relevant measure. Even if the probability of assault on a given trip is very low, repeated exposure to that risk can add up over time.

125. My model produces an estimated probability that a driver-initiated sexual assault occurs on any given trip, based on Uber's own incident data (adjusted for under-reporting) and the total number of rides taken on the platform. If the per-trip assault probability is p and a rider takes N trips in a year, the probability that they experience at least one assault is given by the following formula:

¹⁰⁶ Rates given per 100M rides.

¹⁰⁷ UBER_JCCP_MDL_003313105 at slide 7.

¹⁰⁸ UBER-MDL3084-BW-00000017. Jaylynn Dean Communication Log.

¹⁰⁹ UBER-MDL3084-BW-00000023. ██████████ Communication Log.

¹¹⁰ UBER-MDL3084-BW-00000033. ██████████ Communication Log.

¹¹¹ UBER-MDL3084-BW-00000014. ██████████ Communication Log.

¹¹² UBER-MDL3084-BW-00000012. ██████████ Communication Log.

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$$1 - (1 - p)^N$$

126. This formula reflects the chance of “no incidents” on any trip, raised to the number of trips, and then converted to the probability that at least one incident occurs. Even accounting for underreporting, the fraction p for experiencing an incident is about 15 in 100,000 rides. The p for sexual assault is about 1.25 per 100,000 rides.

127. But recall from Section V that risk is not distributed evenly. It is not distributed evenly across the week, with rides at night on weekends having relative risks 2–3 times higher than the baseline. And it is not distributed evenly among riders and drivers, with female riders who have male drivers experiencing risks 3.5 times higher than the baseline. These risk multipliers bump our per-trip probability of experiencing an incident from 15 in 100,000 to 130 in 100,000. And the probability of a sexual assault goes from 1.25 in 100,000 to 11 in 100,000.

128. These multipliers make a difference. Using this framework, I calculate curves that show the probability of experiencing an incident, for a female rider with male drivers who takes trips at night and on weekends. I calculate the probability from 1 to 120 trips per year. These curves translate the abstract per-trip risk into the quantity that actually matters to repeat riders: the chance that a typical Uber user, taking a reasonable number of trips per year, is sexually assaulted by a driver at least once.

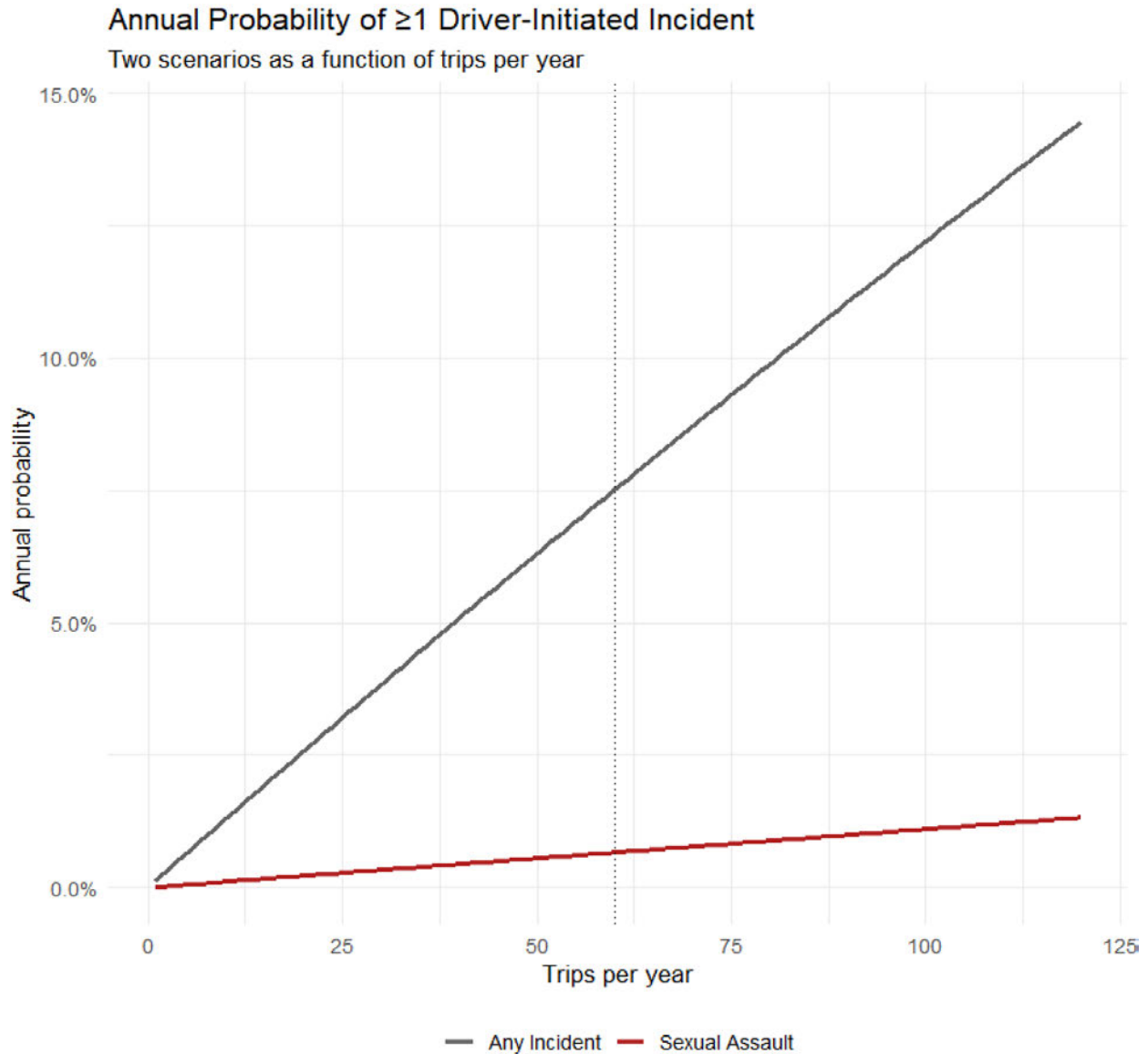
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Figure 10: This graph shows that an individual has a higher probability of a driver-initiated incident happening while on an Uber trip the more Uber trips they take.

129. Using these high-risk conditions (female rider, male driver, late-night and weekend trips), the model shows that cumulative risk rises meaningfully across typical patterns of Uber use. After 20 late-night trips, approximately 1 in 40 women will have experienced at least one incident of sexual misconduct, and roughly 1 in 467 women will have experienced a sexual assault (about 25 and 2 per 1,000, respectively). After 50 such trips, the cumulative probability increases to about 1 in 16 women for sexual misconduct and 1 in 187 women for sexual assault (about 61 and 5 per 1,000). For heavier users taking around 120 late-night trips per year—a level potentially reached by frequent riders—the probabilities rise further to approximately 1 in 7 for sexual misconduct and 1 in 78 for sexual assault (about 140 and 13 per 1,000).

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130. These figures illustrate how different usage patterns translate into different levels of exposure. Occasional riders face non-trivial risks, frequent riders face materially higher cumulative probabilities, and the heaviest late-night users see annual risks that are significant. The underlying per-trip probabilities may appear small when viewed in isolation, but repeated exposure converts these rare events into meaningful annual risks for women who rely on Uber for nighttime transportation and have male drivers.

XII. Extensive Catalogue “Safety Features” do not Alter the Level of Risk

131. Uber has added numerous features to their app over time that have been marketed as safety features. There are also background checks and insurances that are marketed as safety precautions.

132. In 2013, Uber conducted driving and criminal background checks on drivers joining the platform and obtained Rideshare insurance which is blanket non-owned auto insurance.¹¹³

133. In 2014, Uber expanded their background checks to include federal and county specific searches.¹¹⁴

134. In 2016, an internal Uber document shows that the US has the highest rate of Sexual Assaults over time worldwide and the rate of the incidents was on the rise.¹¹⁵ This year Uber also started to mask phone numbers shared between users.¹¹⁶

¹¹³ UBER_JCCP_MDL_001113654 at slide 46. Stand for Safety (Jan. 23, 2018).

¹¹⁴ UBER_JCCP_MDL_001113654 at slide 46.

¹¹⁵ UBER_JCCP_MDL_000031720 at 005.

¹¹⁶ UBER_JCCP_MDL_001113654 at slide 46.

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Sexual Assaults Over Time

135. In 2017, Uber began continuous driver screening, which monitors and flags new criminal activity through a number of data sources.¹¹⁷

136. The in-app Safety Toolkit launched nationally in May 2018 and includes the Trusted Contacts option for riders, which allows them to share their ride information with up to five people, 911 integration including an emergency button in-app and the ability to share real-time locations with police, and the Safety Center to find safety tips and learn about the driver screening process, insurance protections, and community guidelines.¹¹⁸

137. Uber also launched Real-Time ID Check (Mutombo) in the US in 2018 which periodically prompts drivers to take a live photo before accepting rides, using facial comparison technology to verify identity.¹¹⁹

¹¹⁷ UBER_JCCP_MDL_003390040 at 050. 2017-2018 US Safety Report.

¹¹⁸ UBER_JCCP_MDL_000061193 at 193. Email from Tracey Breedon [tbreedon@uber.com] to Rory [rory.kozoll@gotinder.com] re Follow-up from our call sent Nov. 26, 2019 at 11:06 PM.

¹¹⁹ UBER_JCCP_MDL_003390040 at 064.

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138. In September 2019, Uber launched RideCheck nationally with utilized GPS and sensors from the driver's smartphone to detect unusual events, such as unexpected long stops or possible crashes, then would reach out to the rider and driver via the app.¹²⁰

139. In 2020 Uber expanded their sexual misconduct education for all drivers as well as implementing a Survivor support hotline.¹²¹

140. The Dashcam Program can provide dashcams to drivers that record rides.¹²² It includes a Bring Your Own Device (BYOD) program where trips were recorded from the dashboard via the driver's own dash cam.¹²³ This was implemented in 2021 and drivers have to opt-in.¹²⁴

141. Uber launches S-RAD to all UberX trips in July 2022.¹²⁵

142. In August 2022 Uber launches Live Help from a safety Agent in the US, allowing users to request a call or text from an ADT agent who can stay on the phone for the duration of the trip and reach out to 911 if necessary.¹²⁶

143. In 2023, riders and drivers could choose to initiate audio recording of their trip through the Safety Toolkit in the Uber app.¹²⁷

144. Uber experiments in 20 US cities, applying the S-RAD to all rides in September 2023.¹²⁸

145. In January 2024, a widely circulated internal Uber email notes that S-RAD was found to not only be active for UberX trips as designed, it was also active for all mobility products

¹²⁰ UBER_JCCP_MDL_000061193 at 193.

¹²¹ UBER_JCCP_MDL_003390040 at 053. 2017-2018 US Safety Report.

¹²² UBER_JCCP_MDL_000864943 at 946. 2021 Dashcam Program Timeline.

¹²³ UBER_JCCP_MDL_000864943 at 946.

¹²⁴ UBER_JCCP_MDL_000864943 at 946.

¹²⁵ UBER_JCCP_MDL_003274193 at 470. S-RAD Leadership Update (Jun. 17, 2022).

¹²⁶ UBER_JCCP_MDL_003401305 at 306. Driver Safety (Aug. 3, 2023).

¹²⁷ UBER_JCCP_MDL_002260151 at 152. Sachin's Audio Recording Interview Prep Doc (Aug. 2023).

¹²⁸ UBER_JCCP_MDL_002340857. S-RAD Model Transition Experiment by Ben Marchi and Jake Atlas.

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in all active UberX markets and this issue existed since 2020.¹²⁹ At the time it was discovered in early 2024, it was deactivated on non-UberX products with the recommendation to keep it on.¹³⁰

146. Despite continuing to add new features, considering my analysis of both Uber's internal documents and utilizing the Flack raw data, I can say with a reasonable degree of scientific certainty that the platform is no safer than it was previously.

XIII. Conclusions

147. In light of my analysis of the Flack raw data, and the comparison with Uber's internal documents, I can say with a reasonable degree of scientific certainty that Uber had extensive access to information that would have allowed the company to determine relative risk to plaintiffs, but that it did not disclose this data to its riders nor to the public more generally. Moreover, critical aspects of rider-safety, documented by Uber, are not produced in the raw Flack data. As a data scientist, it is conspicuous to me that these important facets of risk were not systematically tracked and produced. The limitations of Flack raw data (by comparison to the internal analysis of risk that Uber noted), suggest that Uber did not fully incorporate the information it possessed on relative risk into its Flack raw data.

XIV. Reservation of Rights

148. My opinions and analysis are based upon the information available to me to date. I may review and consider additional information that may be produced by the parties to this dispute. I intend to supplement my opinions, if it is appropriate to do so. I reserve the ability to provide rebuttal opinions and testimony in this matter, to create demonstratives for use at trial based upon the information contained in this report, appendices, and exhibits, and generally to utilize other graphical depictions as aids in the presentation of my findings.

¹²⁹ UBER_JCCP_MDL_003066057. Email from Margalit Kluger Tamir [margalit@uber.com] to Greg Brown [gbrown@uber.com] et. al re [Action Required by 3/7] S-RAD Product Type Issue - Impact Analysis sent Feb. 29, 2024 at 4:57 PM.

¹³⁰ UBER_JCCP_MDL_003066057 at 058 ("We recommend expanding the current S-RAD model to all non-UberX mobility products...").

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APPENDIX A

RELIANCE MATERIALS

All documents and sources referred to and cited in Dr. Chandler's Opening, Rebuttal, and Supplemental Reports and their footnotes, including Bates-stamped documents, deposition transcripts and exhibits, and other sources, including all sources on their corresponding Reliance Materials lists.

Discovery Responses

All available discovery responses produced within *In re: Uber Technologies, Inc., Passenger Sexual Assault Litigation*, MDLCase No. 3084 (N.D.Cal.), including:

1. Incident Report Classification of Dominant Tickets for 2017-2024
2. Supp. Info Provided by Defs. Pursuant to the Parties' Agreement (4/4/25)
3. Incident Report Classification for 2023-2024
4. Safety Incident Data (produced on 10/13/25 and 10/17/25 into the AWS secure environment administered by BDO)
5. Declaration of Sunny Wong (9/24/25)
6. Am. Pl. Fact Sheet, MDL No. 3084 CRB for Case No. 24-cv-07019, [REDACTED]
7. Am. Pl. Fact Sheet, MDL No. 3084 CRB for Case No. 24-cv-07821, [REDACTED]
8. City_id Values for U.S. Cities

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Deposition Transcripts & Exhibits

Deposition transcripts and exhibits within the matter of *In re: Uber Technologies, Inc., Passenger Sexual Assault Litigation*, MDLCase No. 3084 (N.D.Cal.), including:

1. Todd Gaddis Deposition and Exhibits (11/7/25)
2. [REDACTED] (B.L.) Deposition and Exhibits (6/25/25)
3. [REDACTED] (A.R.) Deposition and Exhibits (7/14/25)
4. [REDACTED] (LCHB128) Deposition and Exhibits (6/25/25)
5. Jaylynn Dean Deposition and Exhibits (6/27/25)
6. [REDACTED] (WHB 832) Deposition and Exhibits (7/10/25)
7. Greg Brown Deposition and Exhibits (8/26/25)
8. Dennis Cinelli Deposition and Exhibits (3/28/25)
9. Gregory Brown Deposition and Exhibits (3/13/25)
10. Mariana Esteves Deposition and Exhibits (7/15/25)
11. Michael Akamine Deposition and Exhibits (5/20/25)
12. Rebecca Payne Deposition and Exhibits (04/02/25)
13. Sunny Wong Deposition and Exhibits (4/16/25)

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Bates Stamped Productions, including:

1. [REDACTED]-CO-000018
2. BW-DEAN_JAYLYNN_000026
3. UBER_JCCP_MDL_000031720
4. UBER_JCCP_MDL_000061193
5. UBER_JCCP_MDL_000061193
6. UBER_JCCP_MDL_000126629
7. UBER_JCCP_MDL_000250826
8. UBER_JCCP_MDL_000251111
9. UBER_JCCP_MDL_000258366
10. UBER_JCCP_MDL_000258366
11. UBER_JCCP_MDL_000308922
12. UBER_JCCP_MDL_000333537
13. UBER_JCCP_MDL_000454790
14. UBER_JCCP_MDL_000509247
15. UBER_JCCP_MDL_000509298
16. UBER_JCCP_MDL_000515739
17. UBER_JCCP_MDL_000516123
18. UBER_JCCP_MDL_000555196
19. UBER_JCCP_MDL_000864943
20. UBER_JCCP_MDL_000960186
21. UBER_JCCP_MDL_001087026
22. UBER_JCCP_MDL_001113654
23. UBER_JCCP_MDL_001113654
24. UBER_JCCP_MDL_001113654

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25. UBER_JCCP_MDL_001562549
26. UBER_JCCP_MDL_001687315
27. UBER_JCCP_MDL_001720345
28. UBER_JCCP_MDL_001733185
29. UBER_JCCP_MDL_001738115
30. UBER_JCCP_MDL_001738115
31. UBER_JCCP_MDL_001741616
32. UBER_JCCP_MDL_001755017
33. UBER_JCCP_MDL_002029470
34. UBER_JCCP_MDL_002249692
35. UBER_JCCP_MDL_002266899
36. UBER_JCCP_MDL_002275608
37. UBER_JCCP_MDL_002279408
38. UBER_JCCP_MDL_002291681
39. UBER_JCCP_MDL_002340857
40. UBER_JCCP_MDL_002613582
41. UBER_JCCP_MDL_002658347
42. UBER_JCCP_MDL_002731221
43. UBER_JCCP_MDL_003066057
44. UBER_JCCP_MDL_003221729
45. UBER_JCCP_MDL_003273474
46. UBER_JCCP_MDL_003274193
47. UBER_JCCP_MDL_003306684
48. UBER_JCCP_MDL_003390040
49. UBER_JCCP_MDL_003390040

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50. UBER_JCCP_MDL_003398058
51. UBER_JCCP_MDL_003398058
52. UBER_JCCP_MDL_003401305
53. UBER_JCCP_MDL_003401305
54. UBER_JCCP_MDL_003504225
55. UBER_JCCP_MDL_003561529
56. UBER_JCCP_MDL_003618304
57. UBER_JCCP_MDL_003703388
58. UBER_JCCP_MDL_003703401
59. UBER_JCCP_MDL_004158548
60. UBER_JCCP_MDL_004167165
61. UBER_JCCP_MDL_004212106
62. UBER_JCCP_MDL_004576556
63. UBER_JCCP_MDL_004605605
64. UBER_JCCP_MDL_004641990
65. UBER_JCCP_MDL_004798192
66. UBER_JCCP_MDL_004920084
67. UBER_JCCP_MDL_005240801
68. UBER_JCCP_MDL_005411897
69. UBER_JCCP_MDL_005550300
70. UBER_JCCP_MDL_005642278
71. UBER_JCCP_MDL_005687325
72. UBER-MDL3038-BW-00048905
73. UBER-MDL3084-BW-00000012
74. UBER-MDL3084-BW-00000014

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75. UBER-MDL3084-BW-00000017
76. UBER-MDL3084-BW-00000023
77. UBER-MDL3084-BW-00000033
78. UBER-MDL3084-BW-000050791
79. UBER-MDL3084-BW-000050792
80. UBER-MDL3084-BW-00008486
81. UBER-MDL3084-BW-00008573
82. UBER-MDL3084-BW-00027901
83. UBER-MDL3084-BW-00028164
84. UBER-MDL3084-BW-00028166
85. UBER-MDL3084-BW-00048509
86. UBER-MDL3084-BW-00048883
87. UBER-MDL3084-BW-00049300
88. UBER-MDL3084-BW-00049301
89. UBER-MDL3084-BW-00049302
90. UBER-MDL3084-BW-00049313
91. UBER-MDL3084-BW-00049317
92. UBER-MDL3084-BW-00050793
93. UBER-MDL3084-BW-00050794
94. UBER-MDL3084-BW-00050795
95. UBER-MDL3084-DFS00003727
96. UBER-MDL3084-DFS00015927
97. UBER-MDL3084-DFS00054771
98. UBER-MDL3084-DFS00054848
99. UBER-MDL3084-DFS00159600

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- 100. UBER-MDL3084-DFS00159622
- 101. UBER-MDL3084-DFS00159626
- 102. UBER-MDL3084-DFS00159672
- 103. UBER-MDL3084-DFS00159678
- 104. UBER-MDL3084-DFS00160119

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Documents considered that were not produced in this case

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2. Jha, P., et al. (2013). "21st-century Hazards of Smoking and Benefits of Cessation in the United States." *New England Journal of Medicine*, vol. 368, no. 4, pgs. 341-350.
3. Mapquest. Business at 2210 N. Scottsdale Rd., Tempe, AZ 85281. <https://www.mapquest.com/us/arizona/zu-izakaya-369010804>.
4. National Highway Traffic Safety Administration. "Seat Belts." <https://www.nhtsa.gov/vehicle-safety/seat-belts>.
5. Pesch, B., Kendzia, et al. (2012) "Cigarette Smoking and Lung Cancer--Relative Risk Estimates for the Major Histological Types from a Pooled Analysis of Case-Control Studies." *International Journal of Cancer*, vol. 131 no.5, pgs. 1210–1219. doi:10.1002/ijc.27339.
6. Spohn C., White C., Tellis K. (2014) "Unfounding Sexual Assault: Examining the Decision to Unfound and Identifying False Reports." *Law & Society Review*, vol. 48 no. 1:161-192. doi:10.1111/lasr.12060
7. Uber. RideCheck: Connecting You With Help When You Need It. <https://www.uber.com/newsroom/ridecheck/>.

HIGHLY CONFIDENTIAL**Appendix B: Classification of Alleged Assailant**

The Flack Incident Data do not contain a single field identifying the alleged assailant. Instead, the data include four ticket-classification fields:

[REDACTED]

As Uber's 30(b)(6) witness Todd Gaddis explained in his November 7, 2025 deposition, Flack consolidates information from Jira and Bliss and applies Uber's internal business logic to determine which ticket is considered the "dominant ticket," and how each ticket is classified with respect to the party it is "reported against."¹³¹ The resulting fields reflect the agent-provided classification, Uber's "inferred probable" classification, a broader "inferred possible" set, and the classification derived from evaluating all associated tickets.

Using the structure described by Mr. Gaddis, I constructed a deterministic alleged-assailant variable by applying decision rules that reproduce the observed mapping between these four fields and the final reported-against outcome. Every distinct combination of these four fields in the Flack dataset maps consistently to exactly one alleged-assailant category (Driver, Rider, Third Party, or Unknown).

The code to implement the alleged assailant classification is included in my produced materials in the file "01_process_flack.r". A description of that logic follows.

1. Classifying the driver as the alleged assailant

An incident is classified as involving a **driver** assailant ("DRIVER") if any of the following hold:

1. The *agent-supplied* field for the dominant ticket indicates the driver:
 - o [REDACTED] == "DRIVER".
2. The age [REDACTED] is not "RIDER" or "THIRD_PARTY". This can occur in several ways:
 - o The "inferred probable" field identifies the driver:
 - [REDACTED] == "DRIVER"
 - o The "inferred probable" field does **not** identify the rider
 - [REDACTED] != "RIDER")
 - a
 - the "inferred possible" field includes a combination in which the driver is one of the possible assailants

¹³¹ Todd Gaddis Dep.

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- (is_driver_pair([REDACTED]), or [REDACTED]), or
- “inferred possible” field does **not** clearly implicate either driver or rider (it is neither a driver pair nor a rider pair, or is missing), and the “all tickets” field indicates that all relevant tickets were reported against the driver:
 - [REDACTED] == "DRIVER"

2. Classifying the rider as the alleged assailant


If the driver logic above is not satisfied, an incident is classified as involving a **rider** assailant (“RIDER”) if any of the following hold:

1. The agent-supplied field for the dominant ticket indicates the rider:
 - [REDACTED] == "RIDER".
2. The age [REDACTED] is not "DRIVER" or "THIRD_PARTY"
 - The “inferred probable” field identifies the rider:
 - [REDACTED] == "RIDER"
 - The “inferred probable” field does **not** identify the driver ([REDACTED] != "DRIVER")
 - a
 - the “inferred possible” field includes a combination in which the rider is one of the possible assailants (is_rider_pair([REDACTED]), or [REDACTED]), or
 - “inferred possible” field does **not** clearly implicate either rider or driver (neither a rider pair nor a driver pair, or missing), and the “all tickets” field indicates that all relevant tickets were reported against the rider:
 - [REDACTED] == "RIDER"

3. Classifying a third party as the alleged assailant

1. If neither the driver nor rider conditions are met, an incident is classified as involving a **third-party** assailant (“THIRD_PARTY”) when:
 1. The agent-supplied field identifies a third party:
 - [REDACTED] == "THIRD_PARTY",
 2. The “inferred probable” field is explicitly **unknown** ([REDACTED] == "UNKNOWN")
 - a

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- the “inferred possible” field does not clearly indicate the driver or rider (it is neither a driver pair nor a rider pair, or is missing), **and**
- the “all tickets” field indicates that all tickets were reported against a third party:
 -  ==
"THIRD_PARTY"

4. Remaining incidents

- Any incident that does not satisfy the driver, rider, or third-party conditions above is classified as “**UNKNOWN**” for the alleged assailant.

In this implementation, the driver and rider conditions are evaluated first, followed by the third-party conditions. Thus, when the available fields are consistent with more than one role, the hierarchy is: **DRIVER**, then **RIDER**, then **THIRD_PARTY**, with any unresolved cases labeled **UNKNOWN**.